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Advanced Fuzzy Logic Heat Pump Controller

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Resumo

Na atualidade, a população está em contacto constante com equipamentos de transformações térmicas de diversas finalidades, muitos destes baseados na tecnologia emergente Bombas de Calor. Nesta dissertação, a importância será dada às suas aplicações para aquecimento de água.

Uma vez que os mercados das Bombas de Calor ainda são emergentes, a procura pela máxima eficiência continua em todos parâmetros. A integração de um controlador “Smart”, dispositivos capazes de implementar de forma isolada ou embutida uma solução de automação completa com recursos avançados como a programação horária, adaptação e aprendizagem, tal como a logica difusa ou as redes neuronais. Neste caso, pretende-se desenvolver um controlador capaz de adaptar-se e aprender os consumos de água do utilizador e como consequência aumentar o conforto do utilizador, e a eficiência global do sistema.

Os controladores de lógica difusa têm grande capacidade de analisar um conjunto de dados ambíguos, incertos e com grande variação entre si. Estes rompem com a tradicional ideia de conjuntos matemáticos e associam o conhecimento humano, o senso comum, e a maneira de o descrevermos o Mundo com a nossa perceção de análise e capacidade de resposta perante situações a controlar e a decidir.

As redes neuronais com características muito semelhantes a lógica difusa, com capacidade de criar padrões, aprenderem e adaptar-se. São soluções baseadas no sistema nervoso Humano, e na capacidade deste aprender e adaptar-se as exigências do ambiente. Solução bastante precisa e com bons resultados, têm sido amplamente usada em sistemas de aquecimento, que são sistemas complexos e não lineares.

Na presente dissertação é mostrado o procedimento realizado na conceção de uma solução passível de cumprir com esse objetivo.

Foi elaborado um modelo do sistema da bomba de calor em “Matlab” e “Simulink” e através do mesmo, projetou-se um novo controlador baseado em lógica difusa em cooperação com uma rede neuronal.

No final deste documento, são apresentados os resultados atingidos, em simulação, pela solução projetada, assim como a comparação e os ganhos conseguidos em relação a uma bomba de calor idêntica mas sem o uso de este controlador “Smart”.

Abstract

Nowadays, especially in developed countries, the population is in constant contact with equipments responsible for Thermal Processing with different utilization purposes, air conditioning, cooling machines, boilers, solar, heat-pumps, etc. In this dissertation, the focus will be given to Heat-Pump System applications for water heating.

The market share of Heat-Pump systems equipments has increased significantly mainly due to their environmental benefits and efficiency. As the market for heat pumps is still emerging, the search for maximum efficiency means that the operation of such systems is optimized at every single point. The integration of a “Smart Controller”, application recent and widely used in various technological areas, a complete automation solution with advanced features like scheduling, adaptation and learning. In this case, it is intended to develop a controller capable of adapting itself and learn the user's water consumption and consequently increase the user’s comfort and the overall system efficiency, for that Fuzzy Logic to the new controller and Neural Networks for the new learning machine will be used.

Fuzzy Logic Controllers have high capability and performance in high complex and non-linear systems with ambiguous data. They reproduce the Human Common Sense and Knowledge about a specific parameter. Breaking with the traditional crisp and sets, Fuzzy Logic Controllers perform their analyses and decision in similar way that users take their actions, in response to state.

Neural Networks have characteristic very similar to the Fuzzy Logic, it has also good performance to deal with high order and non-linear system with ambiguous data. They work as the Human neural system, learning and adapting itself to the external environment. They are capable to create patterns, learn and adapt itself in real time.

In this thesis is shown the procedure performed in the design of a solution which could meet the goal. A model of the system was conceived in Software “Matlab” and “Simulink” which enabled the development, of a Fuzzy Logic based controller in cooperation with a Neural Network, also known in the scientific area by Adaptive Neuro Fuzzy Inference System.

At the end of this document the results, achieved in the simulation at the “Matlab” and “Simulink” Tools by the designed solution are presented.

Acknowledgments

To my teacher and supervisor António Pina Martins by intensive monitoring, guidance, knowledge and support provided in the fulfillment of this dissertation;

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Finally, to Bosch Termotecnologia S.A. for giving me the opportunity of carrying out this dissertation in internship in such good conditions.

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Abbreviations and Symbols

Abbreviations (alphabetical order)

ANFIS	Adaptive Neural Fuzzy Inference System
ASHPWH	Air Source Heat Pump Water Heater
COP	Coefficient of Performance
DEEC	Departamento de Engenharia Electrotécnica e de Computadores
DLS	Damped Least Squares
EU	European Union
ERP	Energy Related Product
FEUP	Faculdade de Engenharia da Universidade do Porto
FL	Fuzzy Logic
FLC	Fuzzy Logic Controller
FR	Fuzzy Rules
GmbH	*Gesellschaft mit beschränkter Haftung* (Company with limited liability)
HP	Heat-Pump
HMI	Human Machine Interface
MSE	Mean Square Error
MF	Membership Function
NN	Neural Networks
NTC	Negative Temperature Coefficient
R	Regression
S.A.	Sociedade Anónima
SC	Smart Controller

Symbols List

A_t	Cross-Sectional Area

A	Superficial Area
C	Heat Capacity
ºC	Temperature Degree Celsius
CC	Corrective Factor due to electric mode
g	Gravitational acceleration
G	Irradiation
h	Heat Transfer Coefficient
h_i	Initial Enthalpy
h_{Top}	Top Enthalpy
h_{Bot}	Bottom Enthalpy
L	Length
M	Mass
$\dot{m}$	Mass Flow
N	Number of Layers
η_H	Heating Efficiency
η_C	Cooling Efficiency
η_D	Discharging Efficiency
q_{cond}	Heat Transfer Quantity of conduction
q_{convec}	Heat Transfer Quantity of convection
q_{rad}	Heat Transfer Quantity of radiation
Q	Heat
Q_a	Heat Power Transmitted to the Hot Source
Q_b	Heat Power Absorbed in the Cold Source
Q_{Hot}	Heat Transmitted to the Hot Source
Q_{Cold}	Heat Absorbed in the Cold Source
Q_{elec}	Total Heat include Looses
$Q_{elec,week,smart}$	Heat Power of Heat Pump System in the Week with Smart Mode
$Q_{elec,week}$	Heat Power of Heat Pump System in the Week without Smart Mode
Q_{ref}	Heat Power of reference Tapping Profile
T	Temperature
T_{amb}	Ambient Temperature
T_s	Surface Temperature
T_f	Fluid Temperature
T_{surr}	Surroundings Temperature
T_{cond}	Temperature in the Condenser
T_{evap}	Temperature in the Evaporator
T_{in}	Temperature Water inlet
T_{out}	Temperature Water outlet
T_{Top}	Temperature at the Top of the Tank
T_{bot}	Temperature at the Bottom of the Tank

T_{ref}	Temperature Set-Point of the Tank
T_W	Temperature in Water Tank Walls
U	Overall Heat Transfer Coefficient
V	Volume
w	Weight of Neuron Input
W	Work
W_c	Compression Power
W_t	Expansion Power
z	Height
α	Absorptivity
λ	Thermal Conductivity
δ	Stefan-Boltzmann constant
ρ	Density
ΔU	Internal Energy Variation

Chapter 1

Introduction

In this chapter it is made an introduction to this thesis. It is presented a brief explanation of the project and the motivation for it, followed by the description of the internship company and also a summary of the first proposed objectives.

1.1 - The Project

The Dissertation is the final discipline of MSc in Electrical and Computer Engineering and provides the opportunity to the students to develop a project in a business environment, in the form of an internship, it results from partnership between the Faculdade de Engenharia da Universidade do Porto (FEUP) and Bosch Termotecnologia S.A, and allows the enrichment of practical and work experience.

The entities involved intended to develop a new control software that will be integrated into a Heat Pump, to a model already on the market and developed, which with appropriate modifications should be able to acquire information from the user profile, water consumption, implementing this way a smart controller with inherent COP (Coefficient of Performance) and comfort increase of HP (Heat-Pump) appliances.

This final report includes, in first place, the introduction and contextualization of the project developed, then the state of the art technologies for the issues addressed, the system description and problems, followed by the procedure and solutions adopted and the final results.

1.2 - Motivation

Nowadays, the population is in constant contact and need of equipments responsible for thermal processing with difference purposes, air conditioning, refrigeration machines, boilers, solar, heat-pumps. In this dissertation, it is discussed the application of HP System applications for water heating.

The market share of Heat-Pump systems equipments has increased significantly, mainly due to their environmental benefits and efficiency. Heat-Pumps don't consume any fossil fuel, thus consequently they don't send any pollutants to the atmosphere and they consume low electricity, so the investment of buying a water heating system based in Heat-Pump will pay back to the user after some time.

As the market for heat pumps is still emerging, the search for maximum efficiency means requires optimization of every aspect. The integration of a SC (Smart Controller), recent and widely used in various technological areas which are devices capable to build in one complete automation solution with advanced features like scheduling, adaptation and learning. In this case, we intend to develop the controller able to adapt and learn the user's water consumption and consequently increase user comfort, and overall system efficiency.

Besides the presented facts, this dissertation is an attractive opportunity to for development and innovation in a leading company which offers excellent conditions and working resources as well as an environment of professionalism and rigor.

Bosch Termotecnologia S.A is the centre of development and innovation of the group Robert Bosch in Domestic Hot Water products. The proposed project aims to use new methods in constant development with known potential which should increase the efficiency and effectiveness of the system and whose domain will certainly be an asset for future projects.

1.3 - Company Presentation

The group Robert Bosch GmbH (known as Bosch), named directly after its founder, Robert Bosch (1861-1942) is a German company founded in Stuttgart in 1886 as Mechanical and Electrical Engineering Workshop.

Currently, the Bosch Group is a leader in global technology and services, active in multiple areas such as: automotive, power technology, industrial goods, construction, and thermo technology. It is has more than 306 000 employees around the world generating revenue of 52.3 billion Euros.

The company success is based on a continuous investment in development, research and manufacturing which promotes the company's future and continuity. The Bosch Group has spent about 4.5 billion Euros in research and development originating to 4700 patents worldwide.

The products and services, of the Bosch Group, are designed and constructed to inspire, to fascinate and improve quality of life by providing innovative solutions.

Bosch Termotecnologia S.A

Under the heading name of Vulcano Termodomésticos S.A., the company started the its activity in 1977, in Cacia, Aveiro, operating under a licensing agreement with Robert Bosch GmbH.

In 1983, the Bosch Group acquired Vulcano, and by transferring expertise and equipments began a process of specialization within the Group.

Bosch Termotecnologia S.A focuses on the design, development, production and marketing of new technology and products at Domestic Water Heaters, including wall-mounted boilers, solar heating and heat-pumps.

1.4 - Objectives

The main target of this project is to develop a new control Software, compliant with the European Standard EN 16147-2011 and ERP (Energy Related Products), able to acquire information from the user profile (Water Consumption) in order to guarantee the maximum comfort, implementing in this way a smart controller with inherent COP increase of Heat-Pump appliances.

Nowadays HP control is based on a user defined set-point, water and air temperature crisp values obtained from sensors. By using a Fuzzy Logic Controller (FLC) it will be able to keep the water at a desired temperature by activating/deactivating the compressor and auxiliary electrical elements, changing the expansion valve aperture and regulating the ventilator and water pump speeds based on the set-point, water and air temperature input, but the control law is implemented incorporating the user experience with Fuzzy Rules (FR).

To understand the user profile a software module should be implemented which will be able to automatically learn the user profile and adapt the Fuzzy Inference Engine.

At the end of this implementation the customer will benefit with a higher COP and also with a smart functionality that provides increased comfort.

The controller should be capable to maintain the temperature close to the reference programmed for every operating condition. It should also guarantee the easy adaptation to new configurations of heat pumps, and the compatibility with the existing hardware or at least with only some minimal modifications.

The values provided by temperature sensors are the inputs to the controller while the output is the actuators reaction to keep the system as desired.

The following image represents a high level of the FLC architecture in relation with a Neural Network (NN) and the low level model, according to the description above.

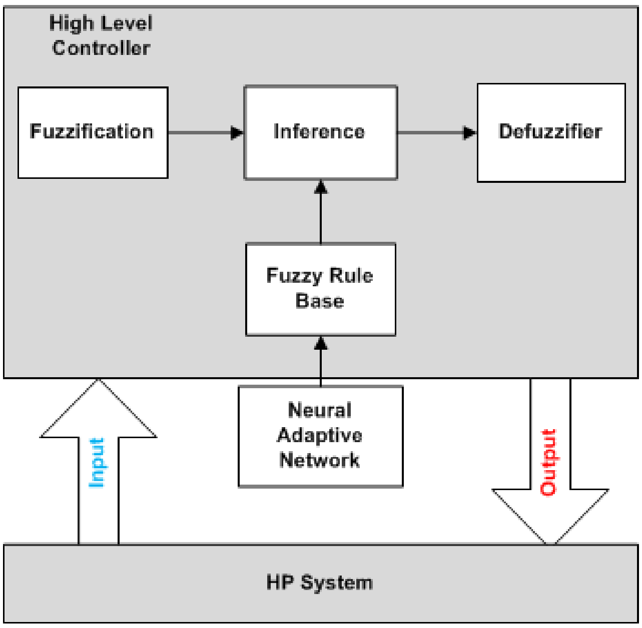

Figure 1.1 – Adaptative Neural Fuzzy Inference System Controller Architecture.

In order to achieve the main goal of having the SC to learn, adapt and control the HP, previously the following objectives were defined:

- Software and HP programming capacities;
- Modelling the HP System;
- Design the ANFIS architecture;
- Simulation of the model plus the ANFIS controller;
- Implementation of the controller in the HP system;
- Testing and Tuning;
- Conclusions - COP Analysis.

1.5 - Document Structure

This document is divided in 4 chapters. Each contains several subsections according to the subjects mentioned.

Chapter 2 – State of Art: A compilation of all study available literature on the topic and contextualization of the current work in stream with academic development. Analyses of the benefits and the weakness of the currents solutions are also performed.

Chapter 3 – System Modelling: Details the proposed solution design, simulation procedure, achieved results and model validation compared to a real HP system. Therefore, the development of the SC and the results from its implementation are shown.

Chapter 4 – Conclusions: Presents an overview of the project; final conclusions are made and also some suggestions about future possible developments and work.

Chapter 2

State of Art

This chapter introduces the theoretical framework that underpins the matters dealt within the dissertation and current state of development of the technologies used. It synthesizes the literature related to the theme of HP's, as well as the development of controllers based in FL and ANFIS, it also analyses the strengths and the weaknesses of current solutions adopted.

This section briefly shows a set of data and knowledge, which constitute the starting point of the study.

It is divided in three main sections: the first one concerns HP in general but focused on the Air Source Heat Pump Water Heater, the second one a review on Thermodynamics and Fluid Mechanics and for the last one refers to FL, NN and integrated ANFIS (Adaptive Neuro-Fuzzy Inference System).

2.1- Heat-Pumps

The development of HP technology was encouraged by the need of a new techno solution after fuel crises that lead to high fuel prices and also due to global ecology concern about the pollution causes from burning fossil fuels and theirs effects to the planet and to human life. The applications of environmental laws also eco-friendly subsidies, from several countries, to diverse products encourage people to install systems able to acclimate and warm water without the need to consume fuel.

The idea at the basis of the appearance of the HP it's the energy transfer in form of heat, from one location to another, thus the HP don't consume any fossils fuels neither send any dangerous pollutants to the atmosphere. HP's have high efficiency comparing the electrical energy consumed and the quantity of heat produced. Comparing the most used domestic water heaters systems, gas, fuel boilers and the HP, in terms of operating costs and energy efficient, HP will show better results, as shown in Fig.2.1.

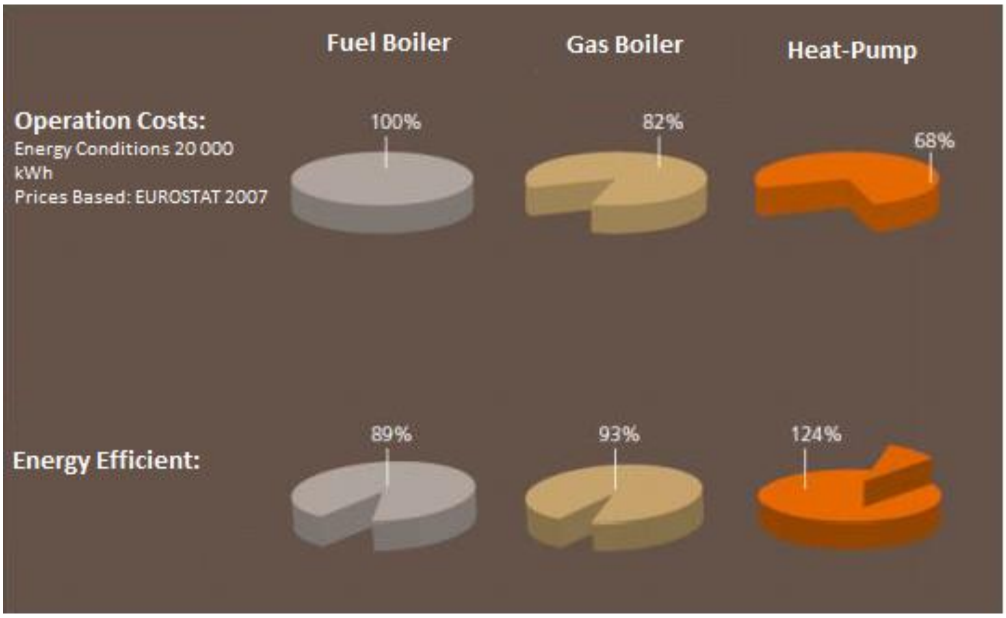

Figure 2.1 – Circular-charts comparing operating costs and energy efficiency among the three most common used solutions [1]

2.1.1- Operation Principle

Heat Pumps technology is based on the Carnot Cycle, which is known from thermodynamics that is the principle most efficiently to transfer heat from two different temperatures, receiving heat from a hot source and sending it to a cold one. In order to contradict the natural impossibility of transferring heat from a lower to a higher temperature it's necessary to provide work to the system and under these conditions we obtain the reversed Carnot Cycle [2] [3].

The ideal Carnot cycle is based on four different phases and is described by the graph in Fig.2.2, the four phases are:

- Isentropic Compression [1-2];
- Isobaric Condensation [2-3];
- Isenthalpic Expansion [3-4];
- Isobaric Evaporation [4-1];

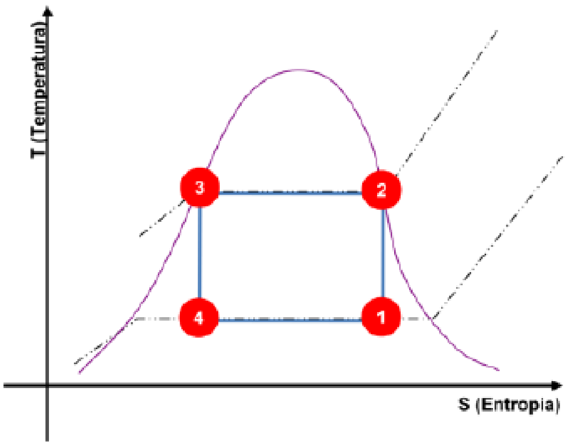

Figure 2.2 – Temperature-Entropy Chart of the thermodynamic ideal Carnot cycle

Although the Carnot Cycle has a high coefficient of thermal transference between two different temperatures, until now unfortunately has not been possible to implement it previously, i.e. the cycle showed in Fig.2.2 cannot be represented in practice, there isn't a Carnot Machine. At HP system this problem has different origins, the most frequently ones are: turbine characteristics, isotherm heat exchangers and the control of set-point, thresholds of condensation/evaporation. Thus, the Carnot cycle implemented at HP is similar to the following:

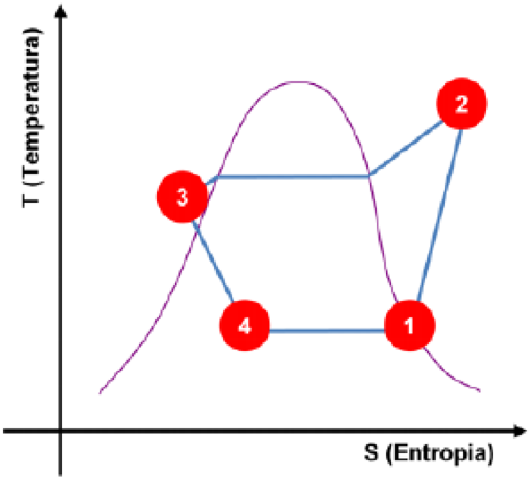

Figure 2.3 – Temperature-Entropy Chart of the thermodynamic Carnot cycle usual implemented

The cycle illustrated on Fig.2.3 comprises the four transformations between the represented points 1, 2, 3 and 4, where:

- Path 1 to 2 adiabatic compression (W_c): The system performs work so that the pressure rises and therefore the temperature of the fluid/gas rises as well;
- Path 2 to 3 isotherm heat exchange (Q_a): Superheated steam is condensed over time, and is in contact with the hot source, it will receive part of the heat released in this condensation.
- Path 3 to 4 adiabatic expansion (W_t): There is no heat transfer in this process; the pressure lowers and consequently also the temperature lowers.
- Path 4 to 1 isotherm Heat Exchange (Q_b): Heat exchanges between the hot source and the fluid/gas, cold source, which receives heat from the external source.

The four processes listed occur through different elements. In the case of the HP, 2 to 3 and 4 to 1, take place through elements that maximize heat transfer between the different surfaces in contact, such as heat exchangers, composed by the condenser and the evaporator. The two remaining steps are achieved using an electric compressor, 1 to 2, and an expansion device, 3 to 4, like a valve.

2.1.2-Operation Cycles

Heat pumps have two main operating cycles, represented in the Fig.2.4 that represents its principal modes of operation: heating and cooling [1].

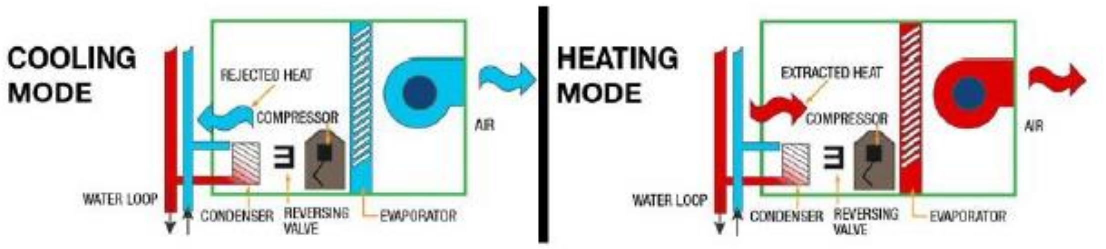

Figure 2.4 – Heat Pump Basic Operation cycles

Heating Cycle:

In the heating cycle, the normal operation is only guaranteed if the coolant is either in liquid or gaseous state.

Initially, the compressor provides work to the liquid/gas which is at low pressure and temperature, causing an increase in pressure and consequently an increase in temperature. Then this superheated gas is cooled, transferring heat to the hot source, and begins the condensation in the heat exchanger, until there is only liquid only at a very low temperature. To finish and restart the cycle, the liquid undergoes an adiabatic expansion in the expansion valve becoming the liquid/gas and is then ready to restarting.

Cooling Cycle:

In the cooling cycle, the basic operation is the same but the heat permutations are inversed compared to the previous explanation, since the objective is also the reverse.

A third cycle may also be considered, known as Defrosting Cycle, but it's a simple iterative changing between the Cooling and Heating cycles, that normally happens to protect the equipment components.

Heat pumps, as already mentioned, has a great advantage the possibility to reverse the cycle, so some solutions may be able to perform both cycles, running either as heaters or as air conditioners.

2.1.3- Components

The HP basic components, Fig.2.5, to implement the Carnot cycle and assure the normal Heat and Cooling cycles are:

- **Refrigerant:** Fluid and/or gas, normally biphasic, with low boiling point. It will be the transporter of the Heat;
- **Compressor:** It's one of the key components and it's responsible to provide work to the system with adiabatic compression to the fluid; The fluid enters the compressor in the physic state of steam and it's compressed to higher temperatures;
- **Expansion Device:** Responsible for the isentropic expansion of the refrigerant; The fluid is expanded returning to low values of temperatures and pressure;
- **Heat Exchanger:** Composed by the Condenser and the Evaporator. It is responsible for the heat exchanges between the fluid and the sources, cold and hot. The condenser isn't more than a plate heat exchanger with two circuits, the hydraulic and the heated refrigerant. The evaporator is a finned tubes heat exchanger, wherein the refrigerant receives heat from the cold source;
- **Fan:** Allows to pull and circulate air inside the Evaporator to increase the heat rate transfer;
- **Temperature Sensors:** General Control of the cycles and prevention of material damage;
- **Accumulator:** Small container that works as buffer to accumulate the heat, it's known in common sense as the water tank;

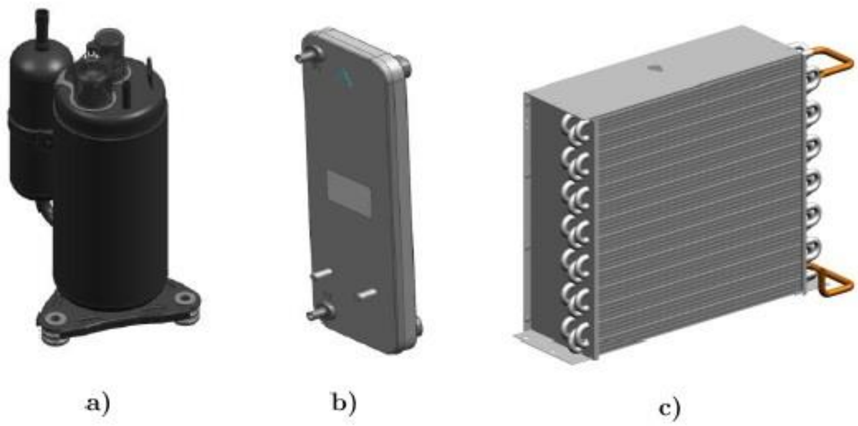

Figure 2.5 – HP Components; a) Compressor; b) Condenser; c) Evaporator;

2.1.4- Heat Sources

The cold source can be from different types: Air, Water or Underground. This choice depends essentially from the follow factors: characteristics of the external environment; limitations of legislative order; income required; cost of installation; time of pay-off, return of the investment [2][4].

Air

It's always available and can be captured from the outside environment or from an inside division of the house. Normally is the cheapest solution as it doesn't need any special equipment or special licensing. Nevertheless the temperature thresholds must be take into consideration, because air temperature under 5-10ºC will drop the COP significantly.

Water

Heat Pumps appliances can also use water as a cold source, under normal conditions all water sources can be used, such as rivers, lakes, sea water or water wells. In the winter, low temperatures can diminish the COP decrease too, or in the worst scenario, if the water gets frozen all HP system can get in dangerous and be damaged.

Underground

Large amount of stored energy can be found on the underground. The source is solar near the surface and geothermal in deeper areas. In specific global regions with volcanic activity the geothermic energy is very high making this solution a very profitable.

2.1.5- Coefficient of Performance

The efficiency of a heat pump can be measured and controlled in well-established tests conditions. The COP value is used as reference result to compare their efficiency the COP is used. The COP is the ratio between thermal energy supplied to the hot source and the work provided to carry out the process. As a first observation we can see that no HP may have a higher COP than the COP of the theoretic reversed Carnot Cycle, the theoretic COP. The theoretic COP is then calculated by the following equations.

$$\mathrm{COP_{Theoric}} = \frac{\mathrm{Q_{Hot}}}{\mathrm{W}} = \frac{\mathrm{Q_{Hot}}}{(\mathrm{Q_{Hot}} - \mathrm{Q_{Cold}})} \tag{2.1}$$

$$COP_{Theoric} \leq \mathrm{COP_{Ideal}} \tag{2.2}$$

From the formulas above it's possible to obtain that in the heating mode, the COP decreases when the outside temperature (Q_{Cold}) gets lower or when the desirable temperature of the system (Q_{Hot}, in the case of HP, water temperature) is very high.

The theoretic COP is a theoretic value refereeing to a machine operating in ideal conditions. To calculate the real COP it must be taken into consideration a corrective factor to the COP, the coefficient of performance.

$$\mathrm{COP_{Real}} = \eta * \frac{\mathrm{T_{cond}}}{(\mathrm{T_{cond}} + \mathrm{T_{evap}})} \tag{2.3}$$

$$\mathrm{COP_{Real}} \leq \mathrm{COP_{Theoric}} \leq \mathrm{COP_{Ideal}} \tag{2.4}$$

In order to avoid over sizing of the system and result in unnecessary costs, each HP should be dimensioned according to the type and purpose it will operate most of the time.

The COP is the coefficient used to compare HP between manufacturers and models in certain markets, such as the European, this COP should remain within a threshold to comply with legislated standards that are very restricted.

2.1.6- Air Source Heat Pump Domestic Water Heater

After discussing the overall operation of Heat Pump Systems, in this chapter the focus will be given on the application which will be the subject of this dissertation, the Air Source Heat Pump Water Heater (ASHPWH). The main characteristic is the addition of a water tank and the possibility to integrate auxiliary heating elements. This water tank will allow reducing of the number of times compressor starts, saving electric energy, and regulating the water temperature.

These tanks are also named as accumulators of inertia and include two main functions: hydraulic separation and thermal flywheel [1]. This separation allows for the independence of the hydraulic flow and the heat flow, because hydraulic and thermal requirements are quite different, especially when used with variable consumption flow rate.

The cycle of operation is very similar to general HP, already explained in sections 2.1.1 and 2.1.2, except that in this case the superheated steam through the condenser is in contact with the water, and the heat is transmitted to it.

The heat transfers to the water in the accumulator and the heated water or the hot source can be performed in different ways. These heat transfers are conventionally classified in indirect and direct heating mode, which will consequently correspond to different ASHPWH configurations.

The most common configurations employed for indirect heating are: immersed tubes or coils in the tank, external shell-and-tube exchanger, and mantle heat exchanger. In the first solution the hot external fluid flows through a coil inserted inside the tank and allows the heat to be transferred to the water inside the accumulator. In the case of an external exchanger, the water is accumulated at the tank and will be pushed by a water-pump to receive heat inside the heat-exchanger and then will return to the tank. Those are the two most commonly used configurations because of their energy and heat transfer efficiency. The mantle exchanger normally provides a large heat transfer area and it’s the simplest and cheapest solution, although its efficiency isn’t as higher as the previous solutions [2] [4].

ASHPWH also allows the possibility to connect external equipments that will increase the performance of the system. These external equipments can be boilers, solar panels which can flow theirs hot fluids to a heat exchanger in contact with water tank, transferring heat to the water, and hydraulic flows from HP and external equipments cannot mix up. Photovoltaic panels can be used to feed the electrical needs of the HP, saving energy costs.

Two schematics of HP are at Fig.2.6 represent the two main used configurations available at markets, coil around the immersed coil.

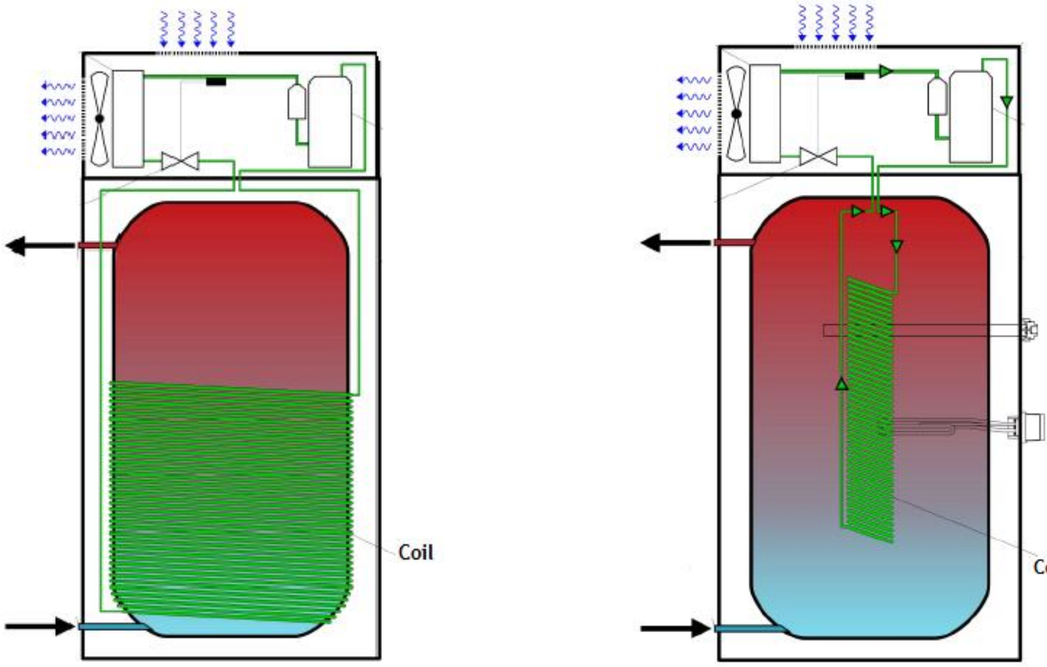

Figure 2.6 – Typical ASHPWH Modules, Coil around the Tank and Coil inside the Tank

2.1.7- EN 16147-2011

The efficiency of a heat pump is measured and controlled in well-established test conditions. In the European market the responsible entity CEN (*Comité Européen de Normalisation*). The standard EN 16147-2011 was proposed to replace the previously EN255-3 and the main changes are: the COP is now lower than before, therefore this change in the requirement it's because now the loses through the water tank are also take into account to the calculation the COP. The second main change is the introduction of five different categories (S, M, L, XL and XXL) to different tank sizes.

The European standard 16147-2011 specifies these same tests and methods for all topologies of heat pump or electric heating including tanks for the purpose of heating water compressors. These conditions are determined taking into account the heat source and the ambient temperature of the same pump. In the Table.2.1 the main conditions and parameters of the test [5] can be observed:

Type of heat source	Temperature in °C (wet bulb)	Ambient temperature for heat pump in °C	Ambient temperature for storage tank in °C
Outside air, indoor installation	7 (6)	15 - 30	20
Outside air, outdoor installation	7 (6)	heat source temp.	20
Indoor air	15 (12)	heat source temp.	15
Exhaust air	20 (12)	15 - 30	20
Water	10 / 7	15 - 30	20
Brine	0 / -3	15 - 30	20
Direct evaporation	4	15 - 30	20

Table 2.1 – Heat Pump Test Conditions by EN 16174:2011 [5]

The standard establishes a sequence of operations to perform in the HP. The six main phases of this test are [5]:

- Heating Period – Time needed to heat the tank from the initial state to the first "reset/turn-off" of the compressor;
- Determination of Energy Consumption at Standby Mode;
- Determination of COP and Energy Consumption for five different test cycles;
- Determination of maximum water temperature and the amount of water usable after a cycle. The water temperature is measure at the exit of the tank after the compressor turns off;
- Operating Temperatures Range;
- Safety Test;

After performing these tests the HP, if the values are in agreement with the defined limits, the HP will receive permission to be commercialized, or get eco friendly benefits from the governments [5].

2.1.8- ERP

The ERP directive, from the European Parliament and Council, it is the standard that defines the labelling of product information, of energy consumption and others resources, to energy-related products [6].

This regulation establishes the requirements for energy labelling and supplementary product information on space or water heaters with a rated heat output ≤ 70 kW. The energy consumed by these heaters exhibits a wide disparity in terms of energy efficiency. Thus, the scope of this standard is to reduce their energy consumptions significantly, to provide incentives for manufacturers to develop energy efficiency heaters and encourage end-users to purchase the best energy-efficient products.

The information provided on the label, Fig.2.7, should be obtained through reliable, accurate and reproducible measurement and calculation procedures that take into account recognised state-of-the-art measurement and calculation methods including, where available, harmonised standards adopted by the European legislation.

Smart Controllers, functionality that automatically adopts the water heating to individual usage will be taken considered a positive factor to the final water heating energy efficiency class.

$$\eta_{wh} = \frac{Q_{ref}}{CC * Q_{elec} * (1 - SFC * Smart) + Q_{corr}} \tag{2.5}$$

$$SFC = 1 - CC * \frac{Q_{elec,week,smart}}{Q_{elec,week}} \tag{2.6}$$

Where Q_{ref} is the tapping profile, CC is a negative factor due to only electrical source, Q_{elec} is total heat including losses, Q_{cor} is the ambience correction term, SFC is the gain due to the use of Smart Controller and the Smart will be 0 if SFC < 0.07 or 1 if SFC ≥ 0.07. Consequently if the Smart Controller provides a good SFC it will improve the efficiency and consequently the ERP class.

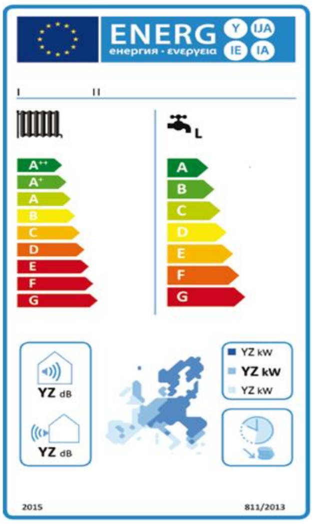

Figure 2.7 – Heat Pump ERP Energy-Label

2.2- Thermodynamics and Mechanic Considerations

In order to understand the Mechanics concepts behind the HP operation and particular the water circuit heat exchanges and flow circulation, a review of basic fundaments about thermodynamics, thermal performance and behaviour of domestic hot water storage tank and thermal stratification is made [7].

2.2.1- Thermodynamics Principles

Thermodynamics is based in a group of physic principles concerned with heat, temperature and their relation to work and energy and the interaction of a system with the surroundings. Thermodynamics focus in the end states of the process during which an interaction occurs. It defines macroscopic variables such as internal energy, entropy and pressure. It is based in four laws that define fundamental physical quantities behaviour under particular conditions, the four principle thermodynamics laws:

Zero Law: If two systems are in thermal equilibrium with a third system, they both must be in thermal equilibrium;

First Law (The law of conservation of energy): due to energy conservation basic principle, the internal energy variation its equal to the total energy received or transmitted to the extern. $\Delta U = Q - W$, where ΔU is the variation of the internal energy of the system, Q is the heat supplied and W the work done by the system.

Second Law: the entropy of any system cannot decrease; such system spontaneously evolves towards thermodynamic equilibrium, state of maximum entropy of the system.

Third Law: The entropy of any pure substance in a thermodynamic equilibrium approaches zero as long the temperature also approaches zero.

Thermal Conductivity (λ – W/m*K): quantifies the ability of a material to conduct thermal energy, heat. Materials with high λ transmit heat at high rate. In this case the two materials of interest are water and air. They have, at ambient temperature (T=27ºC), respectively, λ=0.61 and λ=0.024; Where L is the length, A the area;

$$\frac{\Delta Q}{\Delta t} * \frac{L}{A} = \lambda * \Delta T \tag{2.7}$$

Heat Capacity (C - J/Kg*K): is the relation between the quantity of heat supplied and the variation of temperature observed in a object, is an extensive property of matter, its proportional to the size of the system.

$$C = \frac{Q}{\Delta T} \tag{2.8}$$

These thermodynamics analysis are related to the study of modes of heat transfers and heat transfers rates calculations.

2.2.2- Means of Heat Transfer

A Heat Transfer consequently, occurs every time that exist a temperature difference in a medium or between systems. So, a Heat Transfer is thermal energy in transit due to a temperature difference. This heat movement can be classified in three main modes: Conduction, Convection and Radiation.

Conduction:

The energy transfer by conduction refers to the levels of atomic and molecular activity. It can be seen in a simple way as the transfer of energy from the more energetic to the less particles of a substance due to the interaction between the particles.

Higher temperatures correspond to higher molecular energy, causing neighbouring molecules to collide constantly creating the temperature gradient between the higher energetic to the less energetic.

This molecular activity is more remarkable in gases. However, it also happens in liquids and solids of course. In the liquids, molecular interactions are stronger and more frequent. In the solids, this can be attributed to atomic activity in the form of lattice vibrations.

The Heat Transfer quantity can be calculated in terms of rate equations, i.e., the amount of energy being transferred per unit of time. For one dimensional structure, which has a T(x) temperature distribution the rate equation is expressed in the following Eq. (2.9 – 2.10).

$$\frac{dq}{dt} = -\lambda * \frac{dT}{dx} \tag{2.9}$$

$$\frac{dt}{dx} = \frac{T2 - T1}{L} \tag{2.10}$$

Convection:

This heat transfer mode includes two mechanisms of energy movements, beyond the previously molecular diffusion, also present at conduction. The energy is also transferred in a macroscopic motion of the fluid. It means that any instant large numbers of molecules are moving as aggregates, such motion in presence of a temperature gradient contributes to heat transfer.

When there is a contact between a fluid in motion and a bounding surface with, as result of this interaction, there is the development of a region in the fluid through which the velocity varies, this region is known as “Hydrodynamic” or “Boundary Layer”. Moreover, if the surface and flow temperatures differ there will be a region of fluid through which the temperatures varies and it will become called “Thermal Boundary Layer”. The diffusion energy transfer dominates near the surface of the Thermal Boundary Layer where the fluid velocity is very low, almost zero. On the contrary, the contribution of the motion of fluid will be more felt as more as the flow progresses in the x direction, and eventually transmitted to others layers. This movement of the fluid will play a vital role in our later analysis of convection to design our model.

Convection heat transfers may be caused intentionally or happen naturally path. We speak in forced convection when the flow is caused by external devices, such as fans, water pumps. In contrast, free convection the flow appears due to buoyancy forces, which arises from density differences cause by the difference of temperatures. Both phenomenons are presents in an ASHPWH.

As we described it, the convection energy transfer occurs within a fluid due to these combined effects and it is related to the internal energy. So, including the two mechanisms and regardless the nature of convection, the rate equation is expressed by:

$$\frac{dq}{dt} = h * (T_s - T_f) \tag{2.11}$$

This expression is known as “Newton’s Law of Cooling”, where h is the convection heat transfer coefficient, who depends on conditions such as the boundary layer which are influenced by the surface geometry, the nature of the fluid motion and an assortment of fluid thermal and transport properties.

Radiation:

Thermal radiation is the energy emitted by matter at a finite temperature. It may occur in all physic states, solid, liquid or gases, but is more common in solids. Regardless the form of matter, the radiation emission may be attributed to changes in the electrons configurations of constituent atoms/molecules.

Radiations energy transfer doesn’t need the any material medium. The energy is transported by electromagnetic waves. The radiation transfer processes is modelled by the Stefan-Boltzmann law adapted, the flux emitted by a surface is:

$$E = \varepsilon * \sigma * T_s^4 \tag{2.12}$$

Where (ε) is the radioactive property of the material, emissivity ($0 \le \varepsilon \le 1$). It provides a degree of efficiency of emitting energy comparing to a blackbody, and σ is the Stefan-Boltzmann constant.

Radiation can also come from the outside of the system, from external sources, such as the sun or other surfaces emitting radiation which our system is exposed to. This radiation or part of it may be absorbed increasing the thermal energy of the material. The rate at which this received energy is absorbed per unit surface area may be calculated from the knowledge of the surface's properties:

$$G_{Abs} = \alpha * G \tag{2.13}$$

Where α is the absorptivty, ranging between $0 \le \alpha \le 1$, depending in the material properties.

In Radiation transfers is very common the case of energy exchanges between a small and a very large surface, which involves the smaller one. The radiation heat exchange ratio per unit of time can be expressed and calculated, considering all the situations above, emitted and/or absorbed energy or even surroundings temperatures:

$$\frac{dq}{dt} = \varepsilon * \sigma * (T_S^4 - T_{surr}^4) \tag{2.14}$$

First Law of Thermodynamics and Heat Transfers:

The control Volume is a region of space bounded by a control surface within energy and matter may pass. The first law must be satisfied at each and every instant of time, or over a time interval, i.e. it must exist a balance between all energy rates. The rate at which thermal and mechanical energy enters a control volume, plus the rate at which thermal energy is generated within the control volume, minus the rate at which thermal and mechanical energy leaves the control volume must equal the rate of increase of energy stored within the control volume.

If the inflow and generation of energy exceeds the outflow then there will be an increase of the energy storage. In other hand, if the outflow is higher, then it will decrease the system energy. If there won't be any change in the amount of energy stored.

At an instant of time, applying the energy conservation rule to the control volume, the power specifications, including the rate which thermal and mechanical energy entering, E_{in}, and leaving, E_{out}, and the energy generation on storage must be taken into account to calculate the rate of change of energy stored within the control volume, E_{st}.

$$\frac{dE_{in}}{dt} + \frac{dE_g}{dt} - \frac{dE_{out}}{dt} = \frac{dE_{st}}{dt} \tag{2.15}$$

The inflow and outflow terms are phenomenon exclusively related with processes occurring at the control surface, involving typically heats transfers, fluid flow circulation or work interactions. The energy generator is related to energy to thermal energy transformations by different processes (ex: electric heating caused by current passing at conductor), but also to volumetric phenomenon caused by internal changes at potential energies.

The Eq.2.15 can be related with previous concepts studies of thermodynamics in order to develop more specific forms of the energy conservation requirement equations. As written in the first law of thermodynamics, if over a time interval, heat is transferred to the system, there will be work done in the same amount. In this case, there isn't energy conversion, so $(E_g = 0)$ and potential energy changes are negligible, so the Eq.2.16 will now be reduced to:

$$\mathrm{Q} - \mathrm{W} = \Delta \mathrm{U} \tag{2.16}$$

Other interesting form of the energy conservation law requirement, which is very important and related to ASHPWH, it is when an open system mass flow provides transport of energy into and out of itself. Therefore, the system will have the contribution from the work done by pressure forces of the moving fluid through and the energy storage will be zero, $(E_{st} = 0)$, and so the equation 2.15 will be reduced to:

$$\frac{\mathrm{dm}}{\mathrm{dt}} * \left(\mathrm{u} * \mathrm{pv} + \frac{\mathrm{V}^2}{2} + \mathrm{gz}\right)_{\mathrm{in}} - \frac{\mathrm{dm}}{\mathrm{dt}} * \left(\mathrm{u} + \mathrm{pv} + \frac{\mathrm{V}^2}{2} + \mathrm{gz}\right)_{\mathrm{out}} + \mathrm{Q} - \mathrm{W} = 0 \tag{2.17}$$

2.2.3- Thermal Stratification

After this brief thermodynamics initiation, it will be discussed the thermal behaviour of the water inside storages tanks. In order to sufficient store and use high-quality heat-energy, water tank thermal stratification is widely applied in many kinds of energy storage fields, and the ASHPWH aren't exception [8] [9].

Thermal stratification phenomenon is mostly concentrated in air or liquid mediums. The researches of thermal stratification within the tanks has been studied intensively since the 1970s, motivated from the unsteady characteristics of heating power and consume needs, thermal operation becomes very important in long-term operation of water heating. Its wide application lies in the minimization of the mixing effect which is cause by the thermal buoyancy as consequence of water temperatures differences. Studies showed that the presence of a good thermal stratification may improve the performance of the energy storage up to 6% to 20% by comparison to fully stratified water tanks.

The presence of water tanks in Water Heating systems is due to the difficult to keep in balance the energy requirements, the difference between the actual needs and power of heating, so with its presence it will be able to store energy for this redundancy.

Thermal Stratification Building: a domestic heating water system generally consist of three main parts a heating loop, a user consumption loop and a water storage tank. The heating loop is responsible to heat water to higher temperatures and filled it in to the storage tank, the consumption loop will be active as the user needs or requires of hot water. There are two main situation of thermal stratification building: when there is a hot water tank without external flow and with external flow.

When a hot water tank without external flow is subjected to the ambient temperature, a thermal stratification is formed in the course of cooling process. Thus, the cooler water accumulates at the bottom while hot water ascends to the top, Fig.2.8. This phenomenon occurs even if initially the water inside the tank is at uniform temperature. It is originated from the fact that, prior to the releasing to the ambient the tank walls cools with a thin vertical layer. Part of this heat is transferred by diffusion from the core of the tank and other to the tank walls water [10].

When the heating loop is working the water coming from it is allowed to mix with the colder water inside the tank, causing the supplied temperature to be lowered and the quantity of energy to be decreased, causing the whole tank water to tend to a threshold. The point of using thermal stratification is to eliminate this effect. So when the hot fluid comes from the heating circuit, it will drop on a higher level of the tank where its density matches the density of surrounding fluid. Due to gravity and buoyant effect, water with different temperatures will deposit the corresponding height according to the density difference. Light density will bring the hot water to the top layers and cold one to the bottom. This thermal stratification will work as a barrier separating and maintain vertical temperature gradient. There are other ways to achieve this thermal stratification: heating of vertical walls; heat exchange between the fluids containing within the tank in the same direction of the temperature gradient.

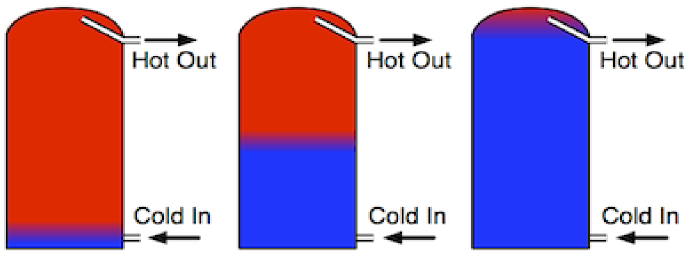

Figure 2.8 – Thermal Stratification within water Tanks, cold water is represented by blue colour and red represents hot water.

Thermal Stratification Perturbations: During the ASHPWH operation, fluid extracted from the bottom of the tank is usually heated and returned to the top of the tank, simultaneous there is a consumption loop which will supply hot water and inject cold water at the bottom with equal rate flow. The turbulence generated by these operations may cause mixing if it is not confined to the right density layers.

Some geometric parameters can affect stratification within the water tank. These geometric factors include tank size, the aspect ratio of tank, and inlet port location and geometry. Moreover parameters related with operating conditions will also affect the thermal stratification, like flow velocity, initial and inlet tank water temperature difference [11].

As main studies about tank geometric parameters, Lavan and Thomson [12], performed experimental studies that showed better thermal stratification can be obtained increasing the relation between the height and diameter of the tank. Others studies suggest that select the height/diameter ratio in interval 3-5, can achieve maximum thermal stratification in the tank. It was also found that the inlet location had a strong influence on thermal stratification while the location of hot water to consumption could be negligible to thermal stratification formation and maintaining cold water inflow at the top of tank will completely mix up the temperature field inside the tank.

The influence of thermal leakage by the tank was also studied. Thermal diffusion through the water tank can be ignored because it doesn't influence significantly the decay of thermal stratification in vertical tanks. However, it was shown that thermal degradation in tanks with thinner walls is more pronounced due to larger axial heat conduction in the tank wall. Following studies on the subject showed that in dynamic mode of operation, the effects of mixing of inlet and outflow water overtake the influence of this parameters, so this effect of wall loses must be taken in account wherein the tank is in static mode or in contact with a cold ambient temperatures.

In the Fig.2.9, it is possible to observe the typical temperature gradients from experimental results in a water tank influenced by the factors described above.

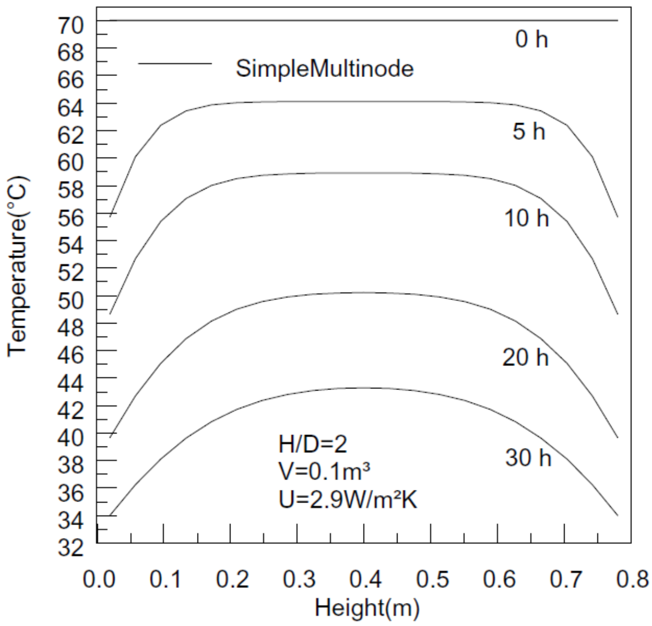

Figure 2.9- Numerical results of temperature along the tank height and time, only natural convection, T_{amb}=20°C and T_0=70°C [14].

Thermal Stratification Performance: In order to assess the efficiency improvement on stratification, a standard should be lied down as a reference. This evaluating index will be difference for each tank and HP behaviour.

For static condition, the stratification number represents the ratio between the means of the temperature gradients at any time to the maximum mean temperature gradient.

The energy efficiency performance of the domestic hot water storage tank is evaluated by calculating the thermal energy stored in the tank and loses.

$$Q(t) = V\rho c_p(T - T_0) \tag{2.18}$$

This energy efficiency may suffer alterations due to the operations conditions of the HP, so three main situations are take into account: heat process, cold process and discharging.

During the heating period, the energy efficiency is defined as the ratio of the energy available at the tank to the energy supplied by the heating module at the instant.

$$\eta_H(t) = \frac{Q_{stored}}{Q_{Heated}} * 100 \tag{2.19}$$

In the cooling period, the energy efficiency is referred to the energy accumulated in the tank at the beginning of the process.

$$\eta_C(t) = \frac{Q_{stored}(t)}{Q_{stored}(t_0)} * 100 \tag{2.20}$$

Finally at the discharging process, the transient discharging energy efficiency is defined as the ratio of the cumulative thermal energy delivered by the water leaving the tank to the initial thermal energy stored at the tank.

$$\eta_D(t) = \frac{Q_{out}\,(t)}{Q_{stored}(t_0)} * 100 \tag{2.21}$$

$$Q_{out}(t) = \int \left(\rho V c_p\right)_{out} * (T_{out} - T_{in})dt \tag{2.22}$$

2.2.4- Modelling

The development of mathematical model is one of the important aspects to study the thermal stratification within the tank. The study of thermal behaviour of the water inside the storage tank can be made either through experimental methods or numerical simulations. Mathematically this problem can be modelled based in the mass momentum and energy conservation equations. The numerical simulation can be implemented using all the differential equations that govern the tank, all its components and all the physical phenomena that occur inside the tank.

Most studies refer and use one-dimensional and two-dimensional models, i.e. related to the water movement's considerations. It is assumed that water can move along the tank in radial and axial directions due to the temperature gradients. The one dimensional models only consider uniform temperature gradient over the axial length and the two-dimensional model considers both motions. The Fig.2.10 shows the typical division and the dynamics factors at the tank.

One-Dimensional: These models are easier, faster, and simple to be implemented in the simulation of thermal stratification and temperature gradient in heat storage tanks. In the basis of these, it is assumed that along the flow direction the tank is divided in L equal elements, layers.

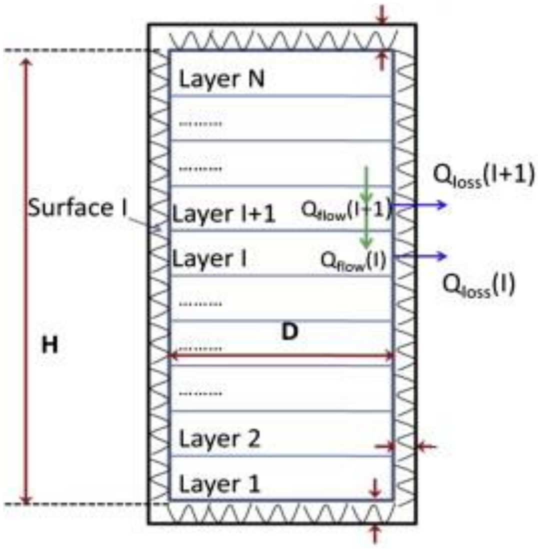

Figure 2.10 – One dimensional schematic, division in N equivalent layers [10].

The first kind of model developed, the temperature-stratified type, consider a factor (δ), which is responsible to determine the position of the incoming flow. This factor will be binary, 0 or 1, and will be controlled by the temperature, comparing between the inlet temperature and the temperature of the actual layer.

$$\frac{dT}{dt} = \frac{\lambda}{\rho * c_p} * \frac{d^2T}{dx^2} + \delta * \frac{\mathrm{dm}}{\mathrm{dt}} * \frac{\dot{1}}{\rho * \mathrm{cp}} * \frac{\mathrm{dT}}{\mathrm{dx}} \quad (2.23)$$

The others models, balanced ones, were built by Alizadeh [13]. The tank is also divided in L equal layers, the cold water enters at the bottom of the tank and is assumed to influence and mix with the 'N' first bottom layers, having no effect on the water in higher position than this point, and the mixing process is neglected by temperature-stratified consideration.

$$T(i,n) = \frac{\left\{\left[V(i) - \left(\frac{\Delta V}{\dot{m}}\right)\right] * T(i,N-1) + \left(\frac{\Delta V}{\dot{m}}\right) * T_{in}\right\}}{V(i)}, i \leq N \quad (2.24)$$

$$T(i,n) = \frac{\{[V(i) - (\Delta V)] * T(i,N-1) + (\Delta V * T(i-1,N-1))\}}{V(i)}, i > N \quad (2.25)$$

In second model developed by Alizadeh [13], heat leaks from the ambient, conduction through thermo-cline and conduction from warm fluid to cold fluid layers conduction through wall and thermal mixing at inlet and outlet are considered.

$$\frac{dT}{dt} = \frac{\lambda}{\rho * c_p} * \frac{d^2T}{dx^2} - \frac{\dot{\mathrm{m}}_\mathrm{s}}{\rho * c_p} * \frac{dT}{dx} * (T_w - T) \quad (2.26)$$

Since the physically movement of water happens in two dimensions, the successful use of one-dimensional models requires the inclusion of certain computational artifices, i.e. procedures that examine at each time step the distribution of temperatures and order them by decreasing temperature gradient. Two artifices with good results are presented by the author Franke [14] multinode with inversion and multinode with mean, respectively.

The multinode with inversion method consists in interchange the segments in a decreasing order, from the top to bottom of the tank, in function of theirs temperature. The highest temperature, at any given time, must be at the top of the tank and all the following layers follow the same rule, then the Layer above will always have higher temperature then the next.

The multinode with mean methods consists on the exempts the temperature inversion by the use of weighted of mean temperature among the layers involved in thermal inversion. In order to do so the layers are scanned in opposite directions and the point of inflexion of the curve is identified in the ascending way. A temperature weighted mean is identified in this layer and the layers immediately above and this mean will be valid for both segments. If a new inversion is identified during the scanning a new mean is calculated and at the end of this algorithm all the layers above the inflexion point will have the same temperature.

Two-Dimensional: These are more complex but also more representative of the reality. The two-dimensional models concern natural and mixed convection, making use of the mass conservation Eq.2.27, momentum in axial Eq.2.28, radial directions Eq.2.28 and energy equations Eq.2.29. The governing equations are normally expressed in cylindrical coordinates due to the normal shape of the tank and to represent the effects of water moving easily. Below are the modelling equations in the simplest version in Cartesian coordinates:

$$\frac{d\rho}{dt}+\frac{d(\rho u)}{dz}+\frac{1}{r}*\frac{d(\rho r v)}{dr}=0 \tag{2.27}$$

$$\frac{d\rho}{dt}+\frac{d(\rho u u)}{dz}+\frac{d(\rho v u)}{dr}=-\frac{d\rho}{dz}+\mu\left(\frac{d^2u}{dz^2}+\frac{1}{r}*\frac{du}{dr}+\frac{d^2u}{dr^2}\right)+\rho g \tag{2.28}$$

$$\frac{d(\rho v)}{dt}+\frac{d(\rho u v)}{dz}+\frac{d(\rho v v)}{dr}=-\frac{d\rho}{dr}+\mu(\frac{d^2v}{dz^2}+\frac{1}{r}*\frac{dv}{dr}+\frac{d^2v}{dr^2}-\frac{v}{r^2}) \tag{2.29}$$

One-Dimensional Vs Two-Dimensional Results: Different studies had compared experimental and real data with one dimensional and two dimensional models. These studies showed that two dimensional numerical simulations are very appropriate since its results were coherent and showed good agreement with the results from the experimental procedures, although their implementation and simulation requires high computational and mathematical analysis.

In the case of the one dimensional methods, simple models differ from actual behavior because it does not stratify the temperature segments in the tank except when there is significant external water circulation. This will be corrected by the use of the computational artifices. Due to this manipulations of the segment temperatures the difference between these results and those obtained with the two dimensional models will be very close. The Fig.2.11 shows the comparison between the One-dimensional and Two-Dimensional results.

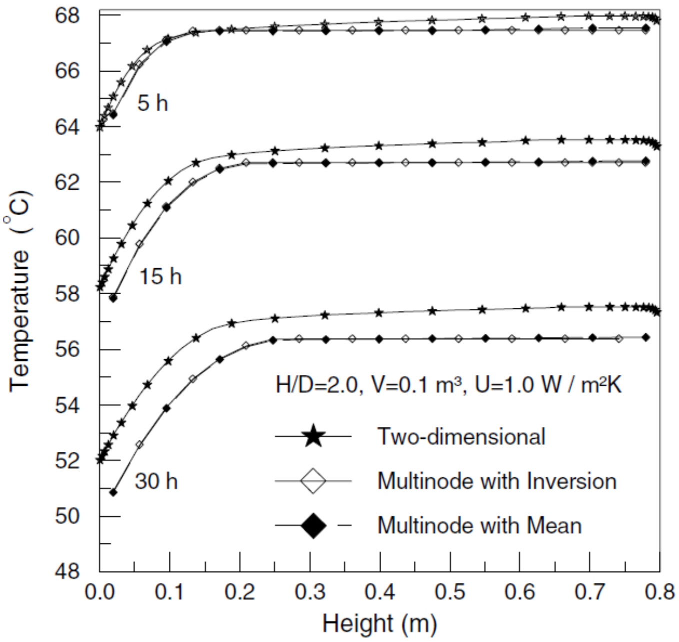

Figure 2.11 – Comparison between one-dimensional multinode with inversion, mean and two-dimensional models. T_{amb}=20°C and T_o=70°C [14].

The one-dimensional multinode models are much faster than two-dimensional models. Thus considering the comparisons there isn't any reason to use two-dimensional methods to simulate in long-term simulations of water heating systems. Nevertheless two-dimensional models can give detailed information about the behavior and are suitable to understand the thermal phenomena in the hot water storage tank.

2.3- Fuzzy Logic

Fuzzy Logic allows control and model systems. It surged as a response to the complex problems of the world, as they need not only mathematical or scientific resolution but also Human common sense knowledge. Thus a FLC will incorporate scientific knowledge with wisdom and general human culture that will influence the final decision of controller.

FL is a simple way to set an output based on inaccurate, vague or ambiguous input information. The method resembles the decision making of a human being, but faster and more accurate [16].

The FL was conceived by Lofti Zadeh, professor at the University of Berkeley in California. It was introduced in 1965, not as a method of control, but as a way of processing information through inaccurate and incomplete sets.

Zadeh's theory is based on the fact that Human beings don't need precise or numerical information to make decisions, and still be highly capable of providing adaptive control to systems. If closed loop controllers can be programmed to accept noisy and inaccurate input they would be even more effective and easy to implement.

In the late seventies, fuzzy logic began to be used in control systems due to the insufficient capacity of the computers of the time. In the early days, the theory was not widely accepted by the system manufacturers.

Nowadays, there are numerous applications of the Lofti Zadeh's concept. It can be found in areas such as control, supervision and monitoring, decision support systems, classification of information, computer vision, pattern recognition and knowledge-based systems.

2.3.1- Fuzzy Sets

The Fuzzy Sets break the traditionally idea that something belongs to a group. Mathematically or traditionally, for example, if it is set that A = {Hot| x≥ 20ºC}, where x is the temperature measure in a room, if the actual temperature in the room is 19.99ºC it won't be considered hot, but 20.01 ºC will. For people this small difference won't probably be felt, but for the mathematical controller it would not reflect the real world and would give a different response in the control system. The Fuzzy Set breaks this paradigm by making the transition between sets gradual, using for this propose the membership functions, " Membership Functions" (MF).

Membership Function

The MF indicates us the belong degree, for each variable to different groups. This degree will be calculated by values from 0 to 1. The MF is defined mathematically by the expression: $A = \{(x, \mu_a(x)) | x \varepsilon X\}$, where x is the valor of variable, μ_a is the MF degree and X is the linguist variable.

A Fuzzy set is completely described by its MF and in the Fig.2.12 it is possible to observe an example of a typical MF of Fuzzy sets.

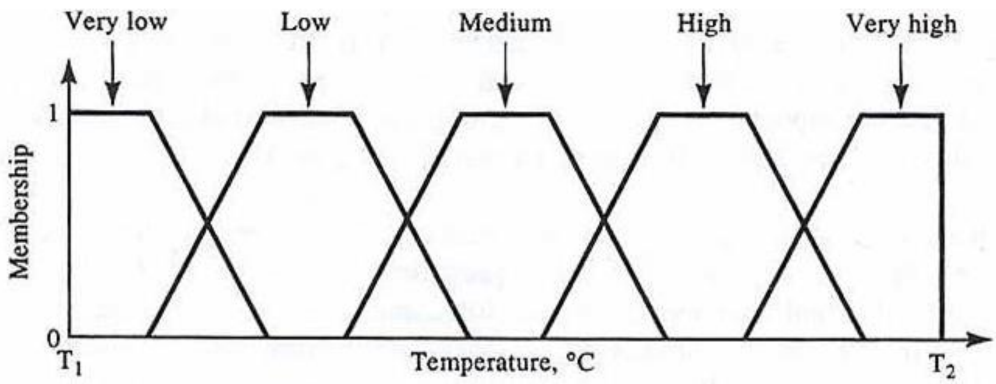

Figure 2.12 – Triangular Membership Functions, Temperature

The MFs have some characteristics that can be useful to describe them or to find specific objectives:

- Support: Set of points where $\mu_a(x) > 0$;
- Core: Set of points where $\mu_a(x) = 1$;
- Crossing Points: Set of points where $\mu_a(x) = 0.5$;
- Fuzzy Singleton: MF made of only one point;

Also, MFs support basic mathematic operations over and/or between them, these operations can be described as:

- Union (OR): C=A U B, $\mu_c(x)=\max((\mu_a(x), \mu_b(x))$;
- Intersection (AND): C =A ∩ B, $\mu_c(x)=\min((\mu_a(x), \mu_b(x))$;
- Negation (NOT): Not C, 1- $\mu_c(x)$;
- Sum: $\mu_{a+b}(x,y)= \min((\mu_a(x), \mu_b(x))$;
- Product: $\mu_{a*b}(x,y)= \max((\mu_a(x), \mu_b(x))$;

Membership Functions can also be represented in different ways and typical forms of MFs, with one dimension, are: Triangular, Trapezoid, Gaussian, Bell and Sigmoid.

The first two forms, triangular and trapezoid, are very simple and used in MF with few linguist variables or small universes. Gaussian and Bell are symmetric and smooth functions, which allow more diversity and complexity and more degrees of freedom. Sigmoid is specific and asymmetric types of functions that allow very high complexity systems and are very used in neural networks.

Linguistic Variable

In the previous example, we talked about Temperature and associated it with a common adjective to describe it, Hot, that's the way FL describes the universe. So, a Linguistic Variable is described by the quintuple (x, T(x), X, G, M), where x is the name of the variable (Temperature); T(x) is the linguistic value that x can take to describe a situation, it's normally a precise adjective (Hot, Cold, etc.); X is the universe ([-5,100] ºC); G is a semantic rule that relates and creates the terms of linguistic value's; M is also a semantic rule that associates to which linguistic variable his value.

Linguistic values can also be related using the operators "AND", "OR", "NOT" as the MF. Beside these it's also possible to use comparative operators "More or Less", "Very" and "Extremely" which are obtained from concentration and dilatation of MF.

2.3.2- Fuzzy If-Then Rules

The rule-base is the main part to develop a Fuzzy Logic Controller (FLC). This rules will define the state and the transition of the system, and also be responsible to determinate the relationship between the inputs and the output of the Fuzzy regions.

A FR, also known as IF-Then takes the form, IF x is A THEN y is B, where x and y represent variables from a MF universe and A and B are their linguistic values, as the basic idea of their behaviour we can see there's a cause and a consequent. Mathematics operators discussed before (And, Or, Not, Sum, Product) can be applying to relate different rules, causes and consequences, which will allow the system to jump and evolve from state to state. The importance of the consequent in the controller's output is calculated by the antecedent.

In cases of FLC, inputs are typically the error and deviation of the error the operations are presented between the linguistic input variables and the output of the controller. The rules presented in Table2.2 bellow show how FLCs operate with linguistic labels of the inputs and output of the Controller. Their purpose is to describe in a qualitative way the control law of the FLC.

IF error is positive AND error change is approximately zero	THEN the output is positive
IF error is negative AND error change is approximately zero	THEN the output is negative
IF error is approximately zero AND error change is approximately zero	THEN the output is approximately zero
IF error is approximately zero AND error change is positive	THEN the output is positive
IF error is approximately zero AND error change is negative	THEN the output is negative

Table 2.2 – Fuzzy Logic Controller table of rules

2.3.3- Fuzzy Logic Controllers

The following scheme, Fig.2.13, shows the typical architecture and steps of a FLC system. It considers three main steps: Fuzzyfication, Inference System and Defuzzyfication.

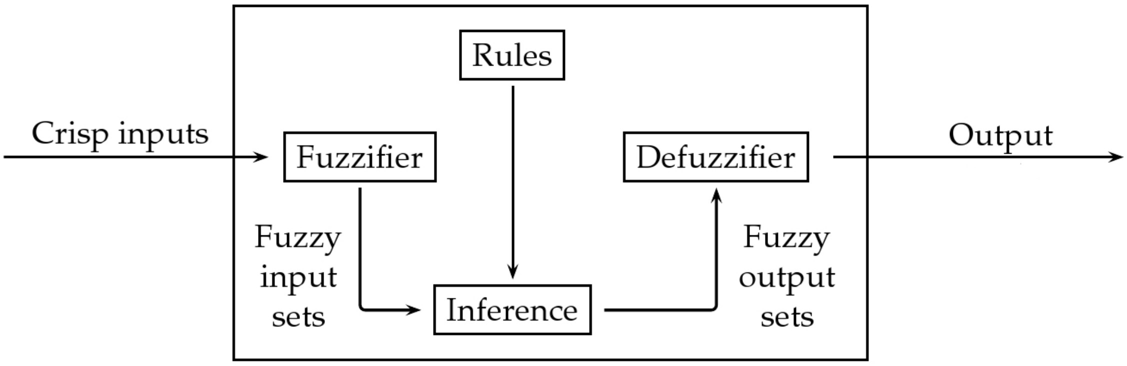

Figure 2.13 – Fuzzy Logic Controller Architecture

Fuzzyfication: It is the first step of the FLC, and it is at this moment that the inputs are acquired and analysed the system state. Therefore the inputs are translated to the respective linguist variables values and theirs MF's and regions created according to the degree of MF in each set.

Inference System: In this stage the If-Then Rules are applied and the resulting region from theirs relation is created. There are two main methods: Mamdani and Takagi-Sugeno.

In the first approach, Mamdani, a region is created through an implication method for each rule. A set whose region size is a function of the weight of the rule is generated for each consequent linguistic variable. It may be seen as a simple association to each numerical input to a fuzzy value. To aggregate all activated regions generated by the rules, the resulting region is the entry to the last stage, it can be represented in Fig.2.14.

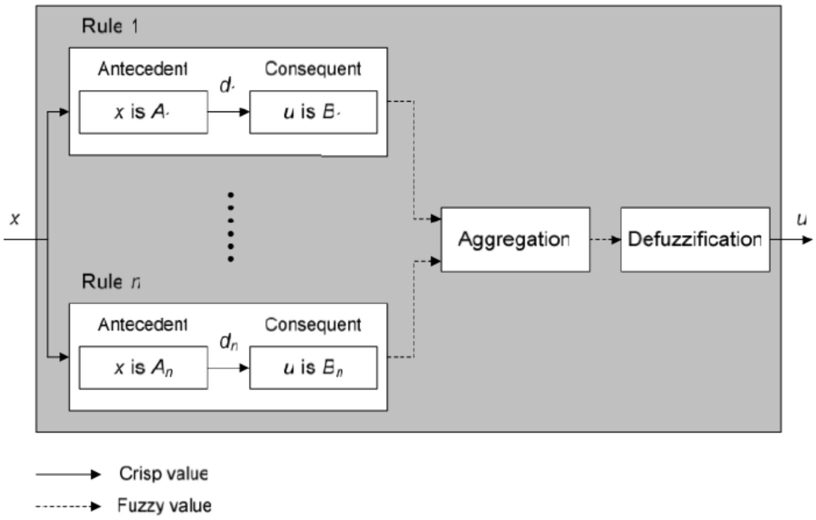

Figure 2.14– Mamdani Inference System [2]

The Takagi-Sugeno method is more complex one, it considers that the consequence of the rules is a function (usually linear) of the last inputs, and then after the calculation of each rule's output, the output is multiplied by the weight of the corresponding proposition. The FLC output will be the sum or the mean of the previously product of each rule. The Takagi-Sugeno inference representative diagram is at the Fig.2.15.

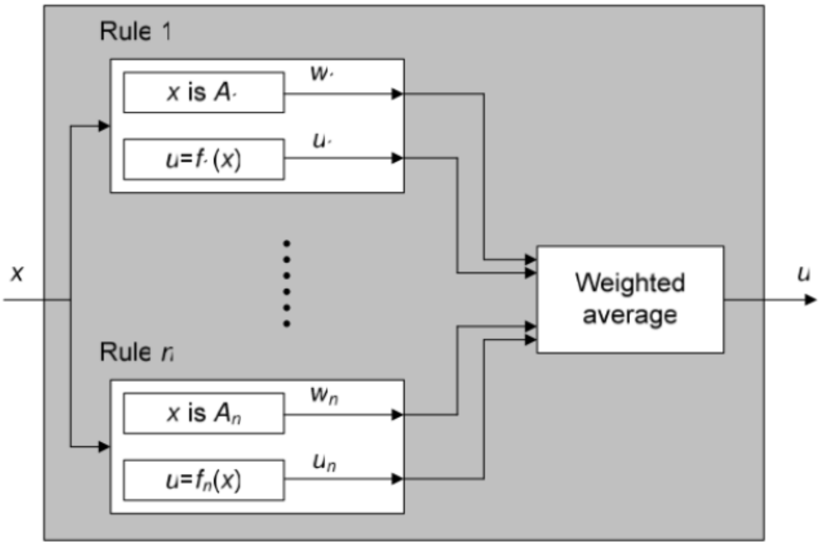

Figure 2.15 – Takagi-Sugeno Inference System [2]

Defuzzyfication: It's the final step of the FLC. The resulting region of the inference system will be converted to the output value of the controller, and it's the matching between the regions and the fuzzy expected value. There are different ways to achieve this defuzzyfication, the most common ones are: Centroid, the centre of mass of the region will be the output; First of Maxima and Mean of Maxima are widely used too.

2.4- Artificial Neural Networks

The central nervous system of animals receives inputs from the outside, stores, processes and transmits information. The observation of these performance features has shown an extraordinary ability to run fast and efficiently highly complex tasks such as processing parallel information, associative memory and the ability to classify an generalize patterns.

These facts served as motivation for both the detailed study of the constitution of the brain and also to design system with the same characteristics and capabilities as the brain, the Artificial Neural Networks (NN). Thus, the NN are aimed mostly to model artificial intelligence, modelling systems through circuits (neurons and connections) simulating the human nervous system, including the ability to learn and act upon the most adverse situations, as well as how to acquire knowledge through experience and observation.

NN first appearance was in 1943, when the neurophysiologist McCulloch developed the first logic, mathematic neuron. In the following years many studies were made in order to reply the brain functions and develop artificial intelligence, capacity to adjust, high number of neurons and neural networks complexity. The applications, in real situations, of these studies were compromised due to the difficulty and complexity in the mathematics involved and the limitations of the computational resources available. In the 80's the NN exploded and had surged the first computational model of supervising and capable of learning NN.

Nowadays, NN can be high complex networks, with billions of neurons, with capacity to learn from the environment adapting automatically and responding to these changes. They can be found in many areas such as control, supervision and monitoring, image processing, robotics, economics and financial analyses, physics as predictive and noise filters [17].

2.4.1- NN Elements

The NN surged based on the Human central nervous system, so as it, the basic components of NN are the brain cells, the Neurons (Computational Units), and the Synapses (Connections between units).

Like the biological neuron, the artificial has one or more input signals and a single output, Fig.2.16. This information may be received by sensors or other artificial neurons that are part of the network. These signals are processed and sent to the output. All input signals should reach the neuron simultaneously.

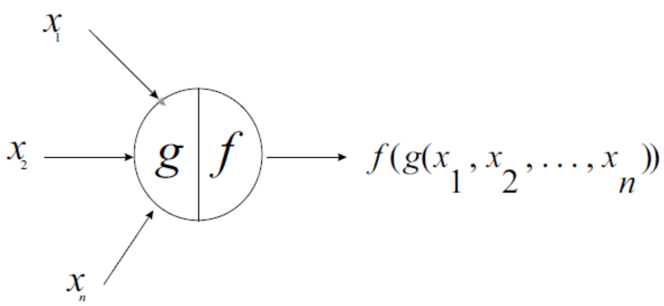

Figure 2.16 – Artificial Neuron Unit

One attribute of major importance in an artificial neuron is the weight, w, represents the degree of relevance that an entry has in the relation to that neuron. The weight value is changed according to the intensity of the input signal and in that way it changes its value to the network. As more stimulated an entry is, more stimulated will be the weight and by consequence will correspond to a more important output in neuron. The excitation signal of the neuron is the product resulting from the sum of the input signals by the weight of their entry.

The next step of the NN is to determine to each neuron if the previously sum had reached the threshold defined, if the threshold is achieved the signal will be transfer to the output. This process is controlled by the transfer function, that as it was seen for each neuron will determinate its state. Normally functions of the following type: step, ramp, Gaussians and/or sigmoid.

2.4.2- NN Architectures

Neurons can be grouped and connected in different layouts, and the NN will respond different and act accordingly to his layout. Normally this group assures the functionality as the human brain, in the way that information can be processed dynamic.

Planar Networks:

The Planar Networks are constituted by hidden-neurons and peripherical neurons, input and output neurons, all arranged in a two-dimensional surface, Fig.2.17. The arrangement of the different neurons may or not be organized in different layers.

The networks with layers are a specific case of planar networks. The network layout will be arranged in parallel layers, the first one will be the input layer passing by the hidden layers going to reach the output layers. The number of hidden layers can be undefined, they are made of neuron as the input or output layer but they aren't in touch with the exterior. The signals are transmitted from one layer to the other by following the transfer functions.

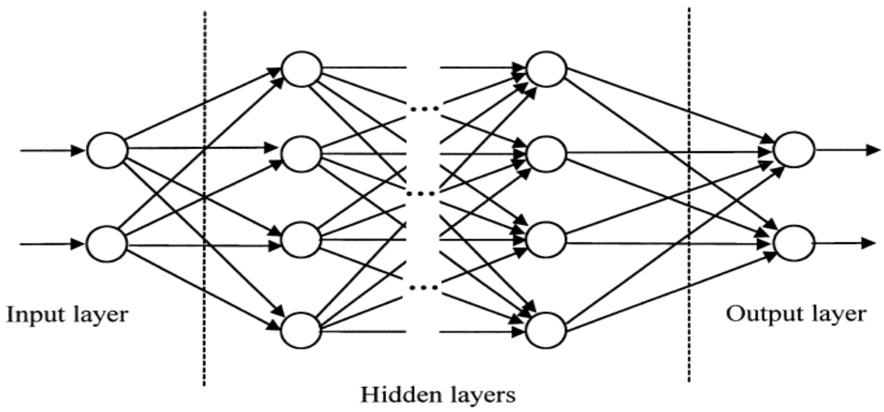

Figure 2.17 – Neural Network Architecture

The information between neurons can also flow in different ways. If the information comes from the previously layer and cannot be an input from a precedent layer, then its a feed-forward network, otherwise it's a recurrent or feedback.

The first type, feed-forward, is very used to develop non-linear models which will be applied to pattern recognition. While, feedback ones are useful to recovery and regeneration of patterns.

2.4.3- Learning

The Learning process is the choice of weights and offsets associated to each neuron and synapse, based in a training showing typical examples of data where the network try to extract relevant information from the patterns. This learning, training process of the network is divided in two main paradigms, the Supervised Learning and the Unsupervised.

Supervised

It is the learning method most commonly used by the NN developed in the World because it requires less computational and mathematic resources and offers excellent results. In this mode, the output desired is known and compared with the actual output of the NN. The weights will be set up randomly at the beginning and will be adjusted by the algorithm on the next iterations.

This rectification of the weights will depend in the relation between the expected and the actual value and the learning method will try to decrease the error in every neuron till the network achieves a precision threshold.

In the supervised mode there's the need of a training mode, so the NN designer must know and have access to accurate and reliable data. The training time will depend on the volume of data presented to the NN. More situations and data volume are associated with betters performance are associated because with less information the weights will be set up for a restrict situations patterns and will fail drastically when a different situation shows up.

Supervised Learning Algorithms: the desired outputs are already known and the weights estimation can be done in two different ways: Reinforcement or Corrective Learning.

The first method, Reinforcement, the weight calculations are done based on the inputs of the network only, when the NN notes that the output isn't the desired one.

In the second method, Corrective Learning, the most frequently used and effective, beyond the inputs the associated error will be used to adjust the setting of weights. The error function generally considered is the MSE (Mean Square Error) and it is a method for estimating the unknown parameters in a linear regression model. This method minimizes the sum of squared vertical distances between the observed responses in the dataset and the responses predicted by the linear approximation, Eq.2.30 shows the mathematical representation of the MSE.

$$E = \frac{1}{2}\sum\sum(o_j - t_j).^2 \tag{2.30}$$

Where o_j is the output vector and t_j is the output target. Associated to this error function there is a mathematic algorithm that command how the learning process will develop. The most commonly used are presented in the following.

Widrow-Hoff Rule: it is the algorithm most commonly used learning process. The goal is to modify the intensity and the importance of the inputs in order to decrease the MSE equation. After transmitting an input to the NN and receiving the respective output and MSE error associated, the Widrow rule will perform a back propagation run based in the derivation of MSE equation. It will affect each layer and consequently changing the weights of the different neurons at the layer reducing the error, this iterative method is also known as simple as Error Back propagation.

For NN with more than two layers the direct application of the Widrow rule cannot be viable, so different iterative and computational solutions to solve this difficult were developed like the derivative or gradient methods.

The objective is to minimize the error changing the weights, so the condition to minimize the MSE will be: $\nabla E = 0$, adjusted in an opposite direction and way of it normal growing. And the weights variation:

$$\Delta w = -\varepsilon \nabla E \tag{2.31}$$

Where, w is the variation between the weights and ε represents the learning rate, described by:

$$w(k+1) = w(k) - \varepsilon \frac{dE}{dw(k)} \tag{2.32}$$

The derivative method will pass the information, in mode Back Propagation mode, based in the follow equations:

$$\frac{dE}{dw.^2{}_{\alpha,\beta}} = (o_\beta - t_\beta) * \frac{df(x_\beta.^2)}{dx_\beta.^2} * f(x_\alpha) \tag{2.33}$$

$$\frac{dE}{dw_{\alpha,\beta}} = \sum(\Delta i * w_{\beta,i}) * \frac{df(x_\beta)}{dx_\beta} \tag{2.34}$$

Software Matlab NN toolbox offers high complexity mathematical methods for training such as Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugate Gradient.

Levenberg-Marquardt: this iterative method also based in the minimization of the MSE error, also known as Damped Least Squares (DLS), is used to solve non linear and complex problems, it’s very effective and runs in short period time comparing to the Bayesian and Scaled Conjugate Gradient.

The calculation of the gradient between the layers interpolates between the descent gradient and the Gauss-Newton algorithm. The Levenberg-Marquardt can be described by the set of equations, second degree approach of E, linear approach of gradient E calculated from the second degree approach and the Gauss-Newton equations:

$$E(w_0 + h) = E(w_0) + \nabla E(w_0)^T * h + \frac{1}{2} * h^T * \nabla^2 E(w_0) * h \tag{2.35}$$

$$\nabla E(w_0 + h) = \nabla E(w_0) + \nabla^2 E(w_0) * h \tag{2.36}$$

$$h = -\left(\nabla^2 E(w_0)\right)^{-1} * \nabla E(w_0) \tag{2.37}$$

$$w(k+1) = (w(k) - (\nabla^2 E\big(w(k)\big)^{-1} * \nabla E\big(w(k)\big) \tag{2.38}$$

Where w is column vector composed by the weights and the network bias, E is the error of LTS and $\mathbf{\nabla E}$ is the gradient calculated from the E, k the layer number index and h is the minimization by Newton.

Unsupervised

The unsupervised learning is still considered as a future option due to its high complexity, it will allow the network to adapt and being in continuous learning and creating an associative memory and pattern recognition.

In contrast with the supervised network, as the name refers, the unsupervised NN doesn't require external help or influences to adjust its weights. However, there is an internal monitoring that tracks the NN performance and if it will develop in a good way and consequently will change the weights to change this trend.

A NN must have a good cooperation between its layers. This cooperation and competition of the neurons is the base of the learning algorithm that will smooth the network to the right output.

Unsupervised Learning Algorithms: in this case, the output is not previously known. The learning mode can be classified in two major groups: Reinforcement algorithms (also present in supervised NN but with slight different in the application), and the Competitive Learning.

Reinforcement algorithms in this case will force the network to respond to an excitation and adjustment of weights to an output with certain characteristics.

The second algorithm, Competitive Learning, the output layer computational units, neurons, will compete for activation, this way for a group of inputs only an output will be active.

Hebb Learning Principle: the Hebb rule is a reinforcement algorithm and associative learning rule. It is based on the assumption that if a neuron is activated by the output of another neuron, they are both active with the same signal and the respective weights of each need to be exited. A changing in a parameter will affect all the sequence neurons which will of course change the output of the NN. This parameter and weight dependence and sensibility will allow the creation of patterns to similar inputs that can be used in pattern recognition problems.

The natural application of Hebb Rule to unsupervised NN can be described by the follow pair of equations:

$$w_{ij}(k+1) = w_{ij}(k) + \Delta w_{ij}(k) \quad (2.39)$$

$$\Delta w_{ij}(k) = \varepsilon * \sigma_i * o_j \quad (2.40)$$

Where σ is a pattern, w is the respective weights responsible to create the σ pattern, and o is the output pattern, and ε the learning rate, (0<ε<1).

There are two computation units based in this Hebb Learning Principle, Fig.2.18, the INSTAR and the OUTSTAR. They are capable respectively produce recognition patterns and information, and to reproduce by stimulation stored patterns, respectively.

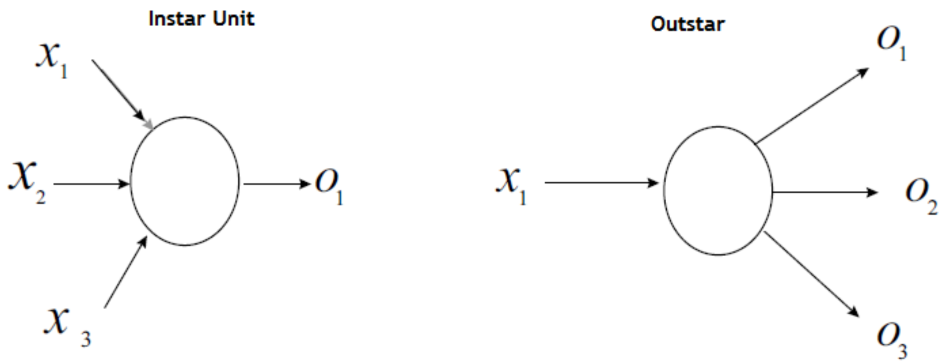

Figure 2.18 – INSTAR and OUTSAR Neurons

Kohonen Rule: the Kohonen Rule is applicable to self-organizing NN which learning algorithm without supervision may be considered as a reinforcement algorithm, competitive learning or even associative learning. The neurons from the network will compete for an opportunity to learn, adjusting their weights. The neuron with best output will be nominated winner and capable to inhibit the competitors weights and/or excite its neighbours. The learning algorithm will focus in the field and range of actuation from the winner neuron. The process begins with a big area which will decrease its size with the progress of the algorithm.

2.4.4- NN and Energy Systems

For the estimation of flow of energy and the performance of systems, analytic computer codes are often used. The algorithms employed are usually complicated, involving the solution of complex differential equations. These programs usually require large computer power and need a considerable amount of time to give accurate predictions. As its known, instead of complex rules and mathematical routines, NN are able to learn the key information patterns within multi-dimensional information domain and are fault tolerant, robust and noise-immune.

Data from energy systems being inherently noisy are good candidate problems to be handled with NN. For those reason, multiples studies and applications in the last years had surged with application of NN to energy systems. NN have been used to modelling and design solar steam generating plants, for the estimation of a parabolic-trough collector's intercept factor and local concentration ratio and for the modelling and performance prediction of water-heating systems. They have been also used for the estimation of heating-loads of buildings, and also to predict air flows and temperatures.

Errors reported when using these models are well within acceptable limits, which clearly suggest that artificial NN can be applied over a wide range of fields for modelling and prediction in energy-engineering systems. In order to develop a reliable and trustful NN is data that represent the past history and performance of the real system and suitable selection of NN models [22].

2.5- ANFIS

The Fuzzy Logic System and NN are both very popular techniques that have seen increasing interest in recent decades. Both methodologies belong to the soft-computing area, which includes approaches to human reasoning and learning that try to make use of the human tolerance for incompleteness and uncertainty, imprecision and fuzziness in the decision making process.

As it was stated in the previous sections, FL and NN share the common ability to deal with uncertainties and noise; both of them encode the information in parallel and distribute it in numerical framework architecture. Therefore, they offer alternatives ways to tackle complex and ill defined problems.

Hence it is possible to combine the advantages of NN with the FL. A network obtained from this association can use of the excellent learning algorithms and use the FL capabilities to interpret in terms of linguistic variables.

Difference structures for FLS and NN association have been proposed and ANFIS is the most known and used.

ANFIS, Adaptive Neuro-Fuzzy Inference System, is a multilayer feed-forward network where each node performs a particular function on incoming signals. Squares and circles are used to represent different properties of adaptive learning, squares represents adaptive nodes. The ANFIS structure is shown at Fig.2.19 and it is normally a five layer network, each layer may have different number of neurons.

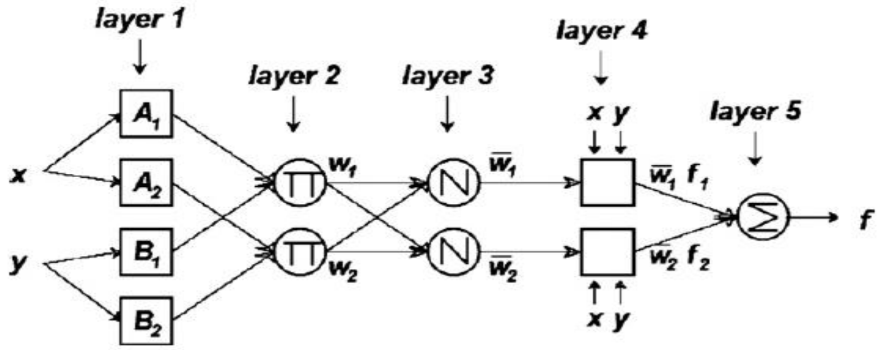

Figure 2.19 – ANFIS architecture

The five layers perform different operations. The first one is responsible to execute a fuzzyfication process, where the input of each node is associated to the linguistic variable and to the respective membership function. On the second layer, the nodes are fixed and play the role of a simple multiplier. This product represents in reality the “And” operation of the Fuzzy If-Then rules, this layer is also called firing strengths of the rules. The next layer, the third, labelled with an N, calculates the ratio between rules strength to the sum of all rules, it normalizes the MF’s. The fourth one has adaptive nodes, the output of each node in this layer it’s simply the product of the normalized values. In the last layer the sum computes the overall output of all incoming signals.

The ANFIS typical shape only has two adaptive layers in his architecture, namely the first and the fourth layer. In each of these layers there are three modifiable parameters. In the first layer they are related to the input MF’s, and are called premise parameters. In the fourth layer, the three modifiable parameters pertaining to the first order polynomial are the consequent parameters. These are the six parameters that confine the adaptive and learning capacities to the ANFIS network.

In this chapter it was performed a deep studied at the HP systems, their configurations, components, advantages and limitations. It was also done a study at the thermodynamics and mechanics to understand how the flow and temperatures gradient acts in thermal stratified tank in order to estimate the flow from the temperature gradient. Different methods and calculation equations to do so were analyzed.

In a second part of it, the high level Control solutions were also investigated in order to develop the main objective, a SC. Fuzzy Logic and it’s capability to treat ambiguous and high order complex problems, the different inference systems, the FR, the construction of the MF’s, the linguistic variables were studied. The learning machine, NN the performance of different architectures configurations, learning methods and final objectives (clustering, pattern recognition, prediction) were also described.

Now that different solutions, knowledge and literature about the topic of dissertation were reviewed and studied it is possible to move to the next phase of this dissertation and start choosing and design the technologies needed to the final objective.

Chapter 3

System Modelling

This third chapter describes the methodology used to achieve a model capable of describing the behaviour of the HP in all operating conditions according to the user water consumption profile. The controller architecture and its simulation are also presented.

This chapter is divided in three sections. The first one introduces the company's prototype and describes its key features for the proposed objective.

In the second section it is presented the adopted solution for the Water Tank and the Hp Heating module modelling and it is made a description of how the different variables and parameters were estimated and determined. The validation of the model by comparing it to the real system is also presented.

The third section is related to the high level of system development, the controller architecture and the reasons behind the adopted solution.

Finally, some considerations are made about the integration of the model with the controller in the simulation and the test results are shown.

3.1- System Specification

In the state of art chapter it was presented different options of HP construction, and several types of components and operations modes. Now the focus will be given to the prototype provided by Bosch which is the target of this master thesis. It is a complete ASHPWH module similar to other products in the market.

The HP is composed by two different main parts: a module responsible for the heating and flow circuits and the inertia accumulator tank. The heating module is composed by the basic components needed to successful implement a Carnot Cycle, which are: one fan, one compressor, one heat exchanger, one water pump and an electrical resistor. There are also two Negative Temperature Coefficient (NTC) temperature sensors to measure inlet air temperature and another located at the fins. The circulating gas is the R135a. Despite the two different constructions configurations presented in chapter 2, immersed coil and coil around the tank, the prototype has a different architecture. In this HP the water enters by the bottom of the tank. Where the temperature is lower it moves through the heating module and returns to the top of the tank.

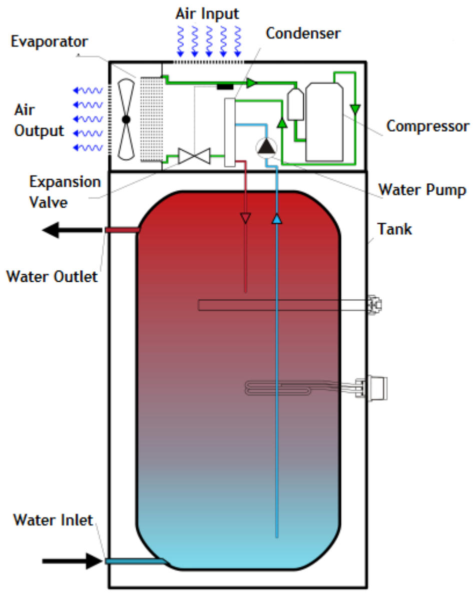

Figure 3.1 – Heat Pump Model Prototype

The water tank has a 260 Liters capacity with an immersed coil that can be connected to auxiliary heating devices (Solar Panels, Boilers) to increase the HP efficiency. There are two water inlet flow ports, one located at the bottom, where the network water enters, and the other is in the middle of the tank allowing the hot water coming from the heating module to mix. It has also two outlet flow ports, one at the top to feed the user with hot water needs and another at the tank bottom to the water-pump and respectively to the Heating loop. In terms of the variables measured, there are two NTC sensors, one at the bottom and another at the top of the tank, to measure water temperature, and the possibility to integrate a third one at the coil, normally used when there's auxiliary heating devices.

Figure 3.2 – Heat Pump Model Construction

The control of these elements is possible through direct action in the Human Machine Interface (HMI), placed at the heating module, that allows to define the heating periods, water set-point temperature and mode of heating (Electric, Heat-Pump or Combi). The HP will automatically begin to work every time that the temperature difference between the top and the set-point is higher than the pre-defined threshold, and only supports ambient temperatures between 5º and 35ºC to work as HP. Water stored in the tank may not exceed 70ºC as this may cause material degradation.

The following Figure 3.2 schematically identifies the main components of the heat pump and their position.

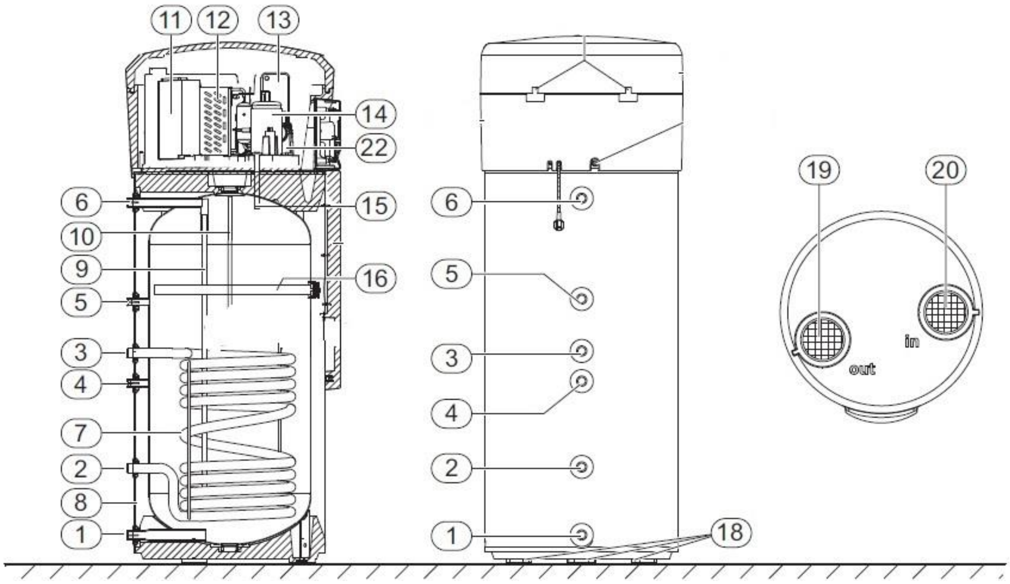

Figure 3.3 – Heat Pump Model Components

(1) Inlet Water Network;	(2) Coil Flow Output;
(3) Coil Flow Input;	(4) NTC Coil;
(5) Recirculation Water;	(6) Consumption out port;
(7) Coil;	(8) Thermal Isolation;
(9) Heat Module Flow-In;	(10) Heat Module Flow-Out;
(11) Fan;	(12) Evaporator;
(13) Condenser;	(14) Compressor;
(15) Sheath for DWH sensor;	(16) Magnesium Anode;
(17) Component Retired;	(18) Support Feet's;
(19) Air-Inlet;	(20) Air-Outlet;
(21) Condensed Output;	(22) Water Pump;

3.2- Model Building

The determination of the mathematical model of a complete generic HP is a complex process that involves highly nonlinear phenomenon and complex thermodynamic equations, due to the multiple components and theirs real-time dynamics. In order to develop the HP model it was used the software "Matlab" and the "Simulink" tool capabilities.

The aim of this dissertation is to acquire information about the user water consumption from the user. However, as the HP under study doesn't have any flow sensor, it is not possible to measure it directly. Moreover the entities didn't want to change or incorporate any new component on the production model. The solution to measure the flow and the water volume difference within the tank will be based from the available top and bottom, NTC temperature sensors, and the temperatures gradient, so as it was seen in the previous researches of the modeling of the water tank dynamics is set by the Thermal Stratification and Thermodynamics principles.

The previous division of the system, a Heat Module and the Water Tank will be considered modeled separately, being integrated together into a final solution.

3.2.1- Heat Module

The heating module is very complex as it has multiple different components (compressor, evaporator, expansion valve, fan, water pump) with connections and dependencies to the external environment and it also correlated to the high level of control, such as, to keep the water at the desirable temperature and available at the times that user has defined.

The HP has three difference heating modes with different heating capacities. The electric mode is constant and proportional to the resistor used, Q=2 kW, although the Heat-Pump mode or the Combi (HP and Electric), are non-linear and they depend from different parameters such as air temperature and water bottom temperature.

In order to model this non-linear relationship in different conditions with high reliability an “User-Friendly” model (previously developed by the company, which takes into account different parameters, such as air temperature, air relativity humidity, fan speed or even compressor and evaporator parameters) was used to determine and construct a look-up table with the relationship between the input air temperature and water bottom temperature and the corresponding outlet water temperature of the heating module. The same procedure was also followed to calculate the COP of each instant.

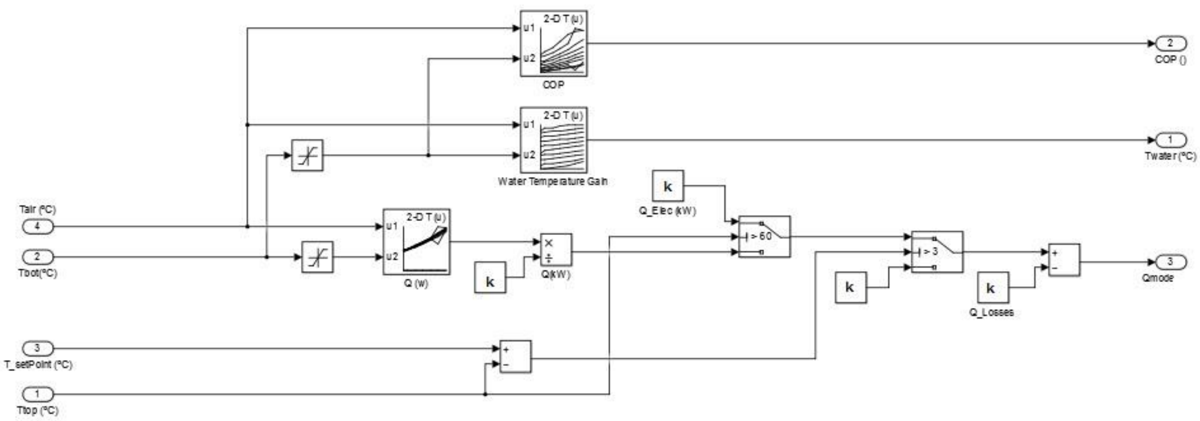

Figure 3.4 – Simulink Subsystem of Heating Module

3.2.2- Inertia Accumulator

As it was seen in the previous chapter there are different options, with more or less complexity, to model the water dynamics within the fully thermal stratified tank, a two dimensional or a one dimensional model. The focus will be on the one dimensional model because of its simplicity and easily, faster to be implemented and reproduced, with highly trustful results.

The first approach to model the water dynamics in time will be by the law of energy conservation from thermodynamics and the one dimensional model. So, if the one dimensional model is being constructed it can be affirmed that the water temperature gradient will be uniform from the top of the tank, where the temperature is higher, to the bottom where temperatures are lower. Thus, the temperature or enthalpy variation will be uniform through the total volume of the tank.

$$\frac{dh}{dz} = \frac{1}{\Delta V} * \int_{0}^{260} hi\, dV \tag{3.1}$$

As the electronic present at the HP only has access to two NTC temperature sensors, then in the real system it can only be used these two temperature measures to calculate the flow. The previous equation will be developed from the point of view of the electronic, even though it may be considering high number of layers to promote the stratification occurrence.

$$\begin{gathered}\frac{dh}{dz} = \frac{1}{2} * (h_{Tot} + h_{bot}) = \\ = \frac{1}{2} * (h_{ref} + cp * \left(T_{Top} - T_{ref}\right) + h_{ref} + cp * \left(T_{bot} - T_{ref}\right) = \\ = h_{ref} + \frac{cp}{2} * (T_{top} + T_{bot} - 2 * T_{ref})\end{gathered} \tag{3.2}$$

The energy movement is represented by the flow circulation. There are two main hydraulic circuits of water flow, the consumption water outlet which will be compensating by the network water inlet. The second water path is the heating module, where water is caught at the bottom at the tank and it returned to the top of the tank. This has a small flow rate comparing to the consumption loop, 3.7 l/min, and will be neglected, although instant energy transfers will be taken into account. Thus, from the conservation of energy equation Eq.3.3 the energy entering in the system will be the water flow from the network, and the output energy is the consumption water and the energy generated by the heat from the heating module.

$$\frac{dE}{dt} = E_{in} - E_{out} + E_g \tag{3.3}$$

Equation 3.3 can be reformulated substituting the energy terms by their components, i.e. the product between the flow and the enthalpy of the water.

$$\frac{dV\rho h}{dt} = m_{in} * h_{in} - m_{out} * h_{out} + E_g \tag{3.4}$$

The flow rate of inlet is the same of the outlet, due to the pressurized tank. Thus,

$$V\rho \frac{dh}{dt} = m * \Delta h + E_g \tag{3.5}$$

The equations 3.2 and 3.5 can now be related and it is obtained the equation 3.6 which will be responsible to model the tank concerning this energy conservation point of view.

$$V\rho \frac{d}{dt}\left(h_{ref} + \frac{cp}{2}\left(T_{top} - T_{bot} - 2T_{ref}\right)\right) = \frac{dm}{dt} * \Delta h + E_g \equiv$$
$$\equiv \frac{V\rho}{2 * (h_{in} - h_{out})} \frac{d}{dt}\left(T_{Top} - T_{Bot}\right) - E_g = \frac{dm}{dt} \tag{3.6}$$

The final equation responsible to model the tank system time dynamics in order to the temperature and flow is achieved and it may be implemented in a "Simulink" subsystem with the above relations between the time, flow and temperature.

The subsystem presented in Fig.3.5, will be responsible to model the energy conservation in segment of the tank and related the real flow to estimated temperature variance, which will be closer to the reality as much our model is representative. This temperature variance will then be used by our HP NTC sensor and the electronic to perform the calculation of the estimated flow. The HP only has access to two temperatures values, so to estimate the flow it can only use the bottom and top layer temperature difference.

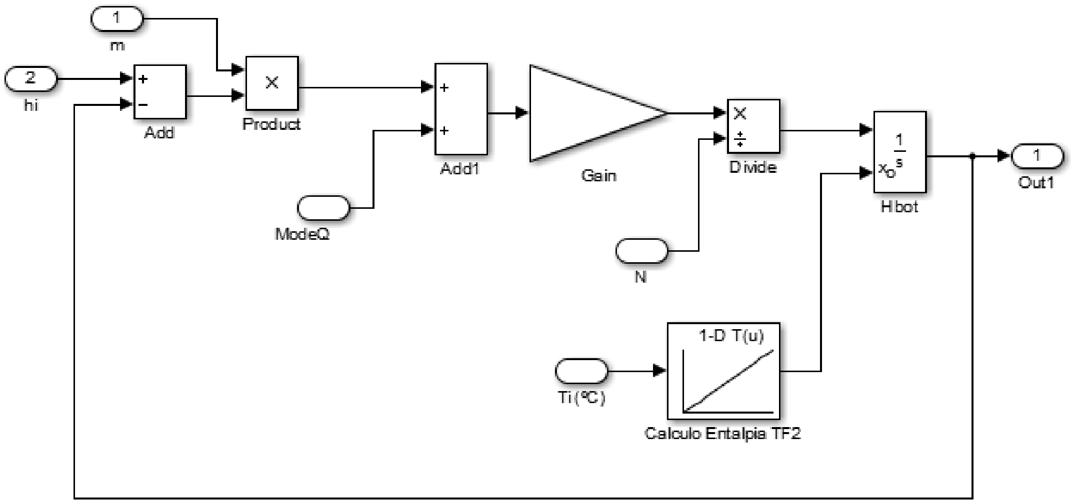

Figure 3.5 – Simulink Subsystem of Energy Conservation Flow-Temperature Equation

The electronic flow estimation block will be based on Eq.3.6. The inputs variables of the block are the top layer temperature and the bottom layer temperature. As constants it is considered the water specific heat, water density, the network water temperature and the volume of two segments, the ones sensors can see. Some extra protection functions are additional to prevent to calculate flow when there isn't any consumption. With long time simulation there will be temperature decreasing due to the loses to the external environment. These protection artifices were made from two different ways in order to achieve the better accuracy, one from temperature differential between top and bottom, which due to tank construction specifications and thermal stratification it is known by benchmark test to be more or less 5ºC difference, so a temperature difference must be higher than 5ºC to be related to a presence of flow otherwise the flow must be neglected. Also from the calculated flow, after system analysis and different simulations it was possible to attribute a threshold to a minimum flow value.

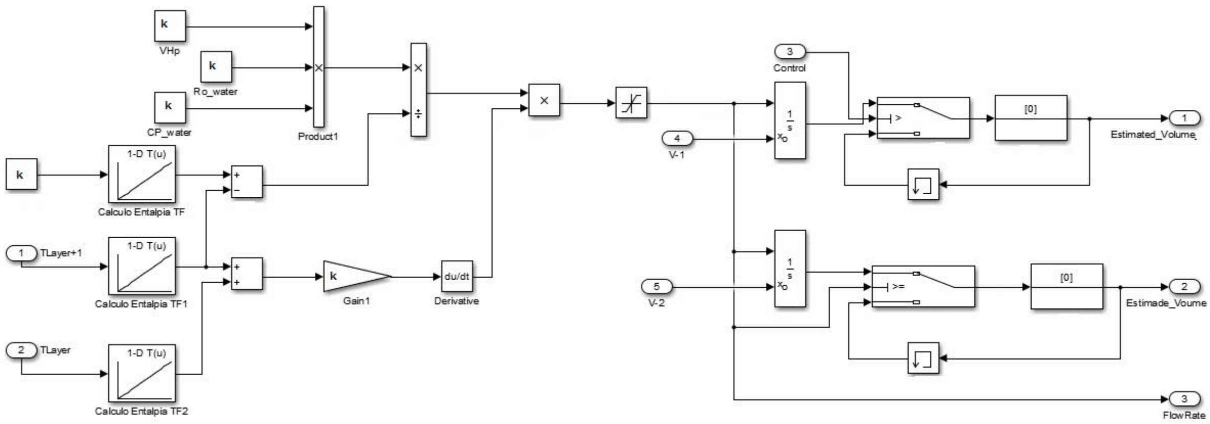

Figure 3.6 – Simulink Subsytem Electronic Flow Estimator

Now that the model of the tank, the heating module and the electronic of HP are finished, we can compare the integrated blocks solution to real data from benchmark tests to validate the model.

3.2.3- Benchmark Test

In order to validate the system model, measure its performance and error rate it must be compared to experimental data acquired from the real system at standard test conditions.

The experimental data were collected during the test conditions of the standard EN 16147 in HP model similar prototype, multiple data was collected and the parameters which it will be focused on are: Tank Temperature, Outlet Water Temperature, Inlet Water Temperature, COP, Heat Power and Tapped Volume (Liters). Although the market product doesn't have a flow meter, in the test to measure the tapped volume one is include so it can have a trustful measured value.

It consisted in 4 standard cycles: Heating Up, Standby, COP and V40. The test were made to a set-point temperature of 54ºC, with a sanitary cold water inlet at 10ºC and a constant ambient temperature of 7ºC.

Validation Energy Conservation Model

After the experimental data is treated and it is known how the experimental results were obtained the simulation of the model can be forced to run in the same conditions to compare the results and check if the error and performance of it is in range of acceptable.

The first observation is to verify if the tank model is doing the thermal stratification between the layers, without thermal loses to the external environment or circulation flow. For that purpose, it simulated a tank, with 4 layers, with initial temperature at each of them with 5ºC difference, from 45 to 60ºC during 24h. In the Fig.3.7 it is possible to see that the temperatures will tend to a value between the two extremes, so the layers are mixing well and the tank is well modulated. The next basic test will be to insert the loses to environment. All the previous layer on long time simulation must start lowering their temperature, even the last layer, which is normally at higher temperature than the exterior.

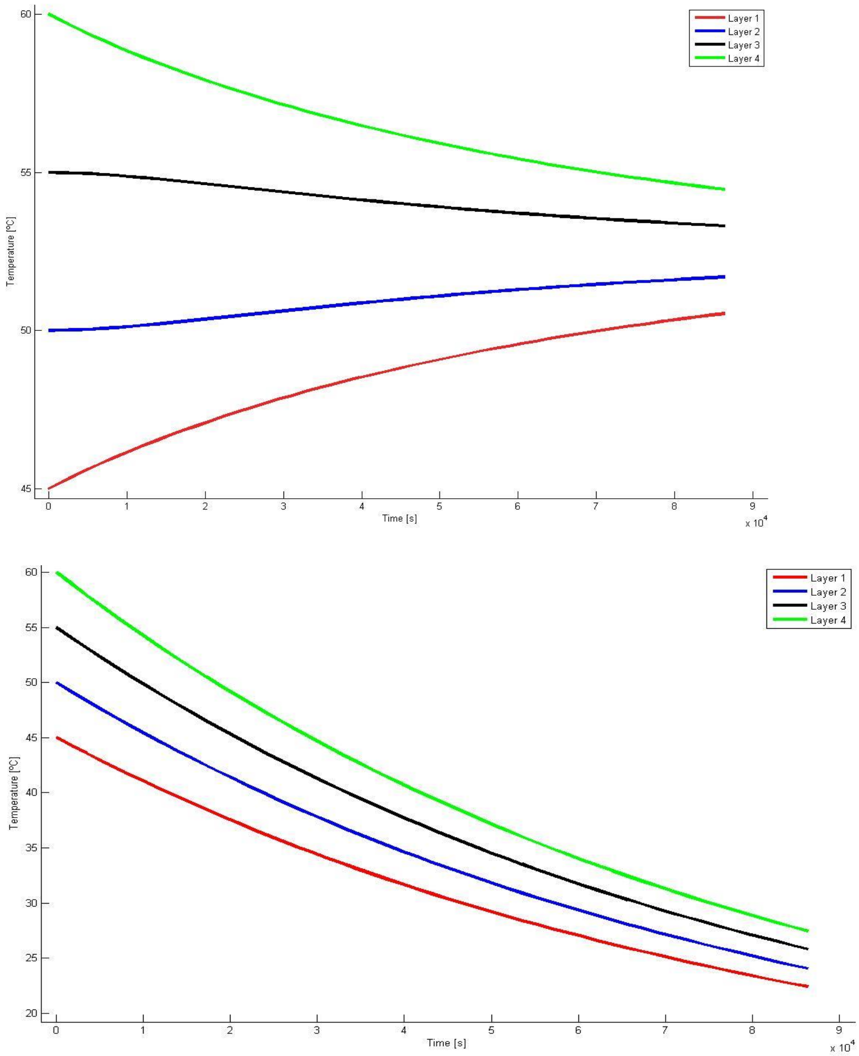

Figure 3.7 – The first graph represents layers temperatures with no looses, the second one temperatures gradient in a day with thermal looses to environment. T_{amb}=10ºC

Finally it was inserted the flow, and the model is now completed with all parameters. Now it's time to validate the flow estimation, temperature differences using the real flow from experimental data and the control signals of the HP mode on real time.

Unfortunately, when it was inserted the last parameters in long term simulations the results were completely different. The flow estimation wasn't much affected by this error, but the temperatures within the tank were completely different, which in long time simulations would affect also the flow estimation and the data it wouldn't be reliable source. These differences are due to the mode of operations and the internal exchanges inside the tank, after a big heat up, even there's consumption the instant after, the water within the tank is still exchanging temperature between them what will make that water inlet won't have as much impact as the heat up didn't happen. This kind of situation was not well modeled by the energy conservation approach, and long time simulations couldn't be made and to simulate weeks or days of use of the appliance.

Since the previously model results were affected by a significant error rate, achieving some very low performances and danger at some operations conditions, that will have a negative impact at the consumption estimation, another model approach will be tried, since the primary objective is to implement later the new Smart Controller, the software simulation must be the closest possible to the reality. Only in that conditions the simulation results and their performance can be trusted to analyze if it pays off to develop a new solution.

To achieve this high performance it is used in the thermal stratification one-dimensional models with computational artifices presented in the state of art, chapter 2. The tank will be divided in N equal segments. These models are very used in some commercial software and normally give good results, although they are more complex and require more computational resources then our previously approach [14].

The Eq.3.7 is the differential equation that is used to discretize each tank segment and construct the inertia accumulator model.

$$Mc * \frac{dT}{dt} = \frac{dm}{dt} c\Delta T + kA_t\Delta z * \frac{d^2T}{dz^2} + UA(T - T_{amb}) \tag{3.7}$$

In this equation M represents the mass of water in each layer, T is the water temperature, $\dot{m}$ is the mass flow rate crossing the segment, A_t is the cross-sectional area, A is the superficial area of each tank segment.

The flow rate across segment will be calculated from the outlet flow which is being transmitted to the segment immediately above, and the received by the one below. In the boundary layers (the topper and the bottom layers) it is used the outlet flow to consumption and the network inlet flow respectively.

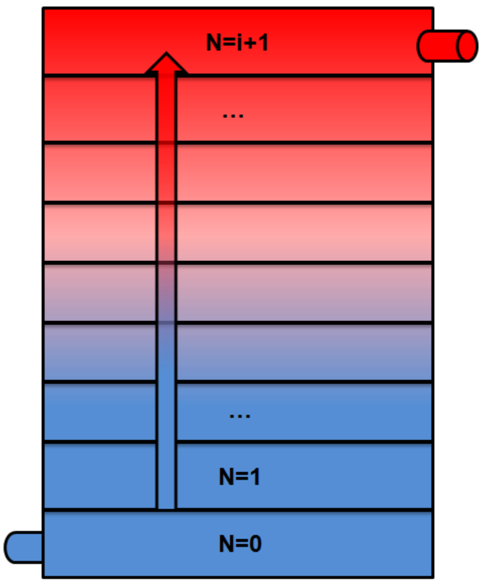

Figure 3.8 – Flow movements in layer Division Thermal Stratified Tank

The temperature gradient will work in the same way that flow do, i.e. the ΔT difference will be between the layer immediately above and the actual, in the boundaries outlet water temperature and network water temperature is considered. The second order derivative term will expand to Taylor series expansion expression, which represents the gradient. If it is considered that the height is measured from the bottom (N=0) to the top (N=i+1), as shown in Fig.3.8, the layers segments will be also incremented in ascending order, the Taylor series will be respectively:

$$\frac{d^2T}{dz^2} = \frac{2T_i - T_{i_{-1}} - T_{i_{+1}}}{\sigma} \tag{3.8}$$

Thus, the equation is simplify and it's responsible to model the fully stratified tank system dynamics in a one-dimensional model, in order to the temperature variation and to estimate the tapped profile, and it may be implemented a "Simulink" subsytem to model the equations above, Fig.3.9.

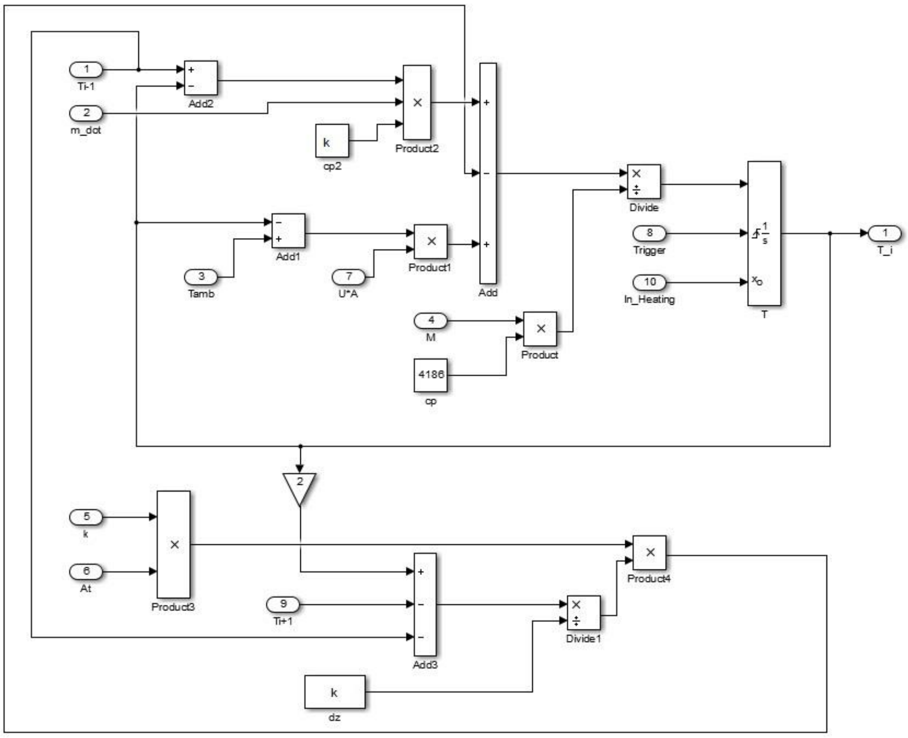

Figure 3.9 – Simulink Subsystem of Thermal Stratified One-dimensional Model

The successful of one-dimensional models require the inclusion of computational artifices, i.e. procedures that for each time step analyze the distribution of temperatures. These procedures don't have a physical base, but does have an interesting practical effect that provides good approximation of the simulated results to the experimental. It is known that only implementing one of the computational artifices and with its incorporation it can be assured that one-dimensional model will give trustful results.

From the methods presented it will be focused attention to the algorithm of Franke [14], multinode with inversion. The method assumes that the highest temperature must be always at the top of the tank and never layer from above can't have lower temperature then any of the layers bellow. To assure this a function will be created to be responsible, at studied specific rate, to analyze and compare the layers temperatures and order them by decreasing order from the top to the bottom.

The “Simulink” subsystem blocks developed to the previously model approach of the conservation energy of the Electronic Flow Estimation and the Heating Module were preserved since the problem and error weren’t directly related to these subsystem but to the tank model.

Validation of the One-Dimensional Thermal Stratification Model

Now that the One-Dimensional tank model with computational artifices is implemented at the “Simulink” with the heating module and the electronic of HP, it can be compared to the integrated blocks solution to real data from benchmark tests to validate the model.

The base tests were also performed to the energy conservation model with success and very close to experimental and real results.

A full cycle is going to be implemented, retired from the benchmark test of the EN 16147 COP. With a initial tank temperature of 54ºC, inlet temperature mean of 10ºC and 10ºC of air temperature. The total tapping after the test was 250 liters. The following figure, Fig.3.10, shows the tapped volumes, the real from the benchmark and the estimated from our temperature gradient. There’s a small difference (error) between them. At the highest point it achieved an error bellow than 5%, which is very acceptable.

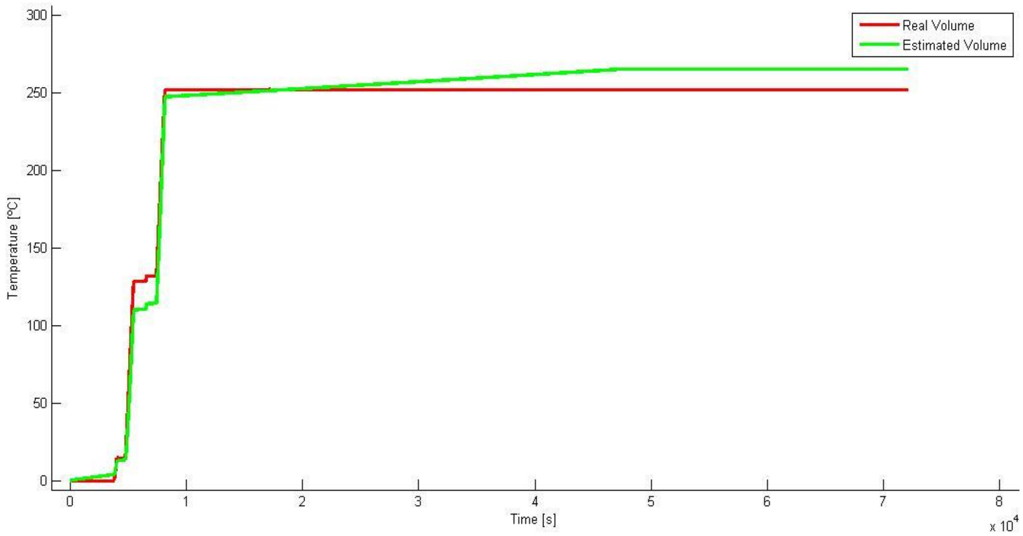

Figure 3.10 – Estimated Volume Vs Real Volume

The results are very close to each other although there’s a small difference. There is a delay between the estimated volume and the real one. This may be explained by that the real volume is directly measure with a sensor, so it’s almost instantly read by the electronic. The model estimation is calculated from the temperature gradients, $\dot{m} = f(T_{top}, T_{bot})$, which takes some times to stabilize in thermal set-point by consequence of water mixing. The temperatures at the bottom of the tank will suffer temperature variation very fast at the beginning of the consumption, but the uppers layers will take more time and are less affected by this gradient. In order to solve this imprecision the parameters need to be adjusted to minimize it. By observation of multiple simulations results with different conditions tests, it was possible to realize that there are different slopes in temperature gradients at the different layers which will be difference when the total water consumption is higher as the simulation times passes. A function g, $\dot{m} = g(f(T_{top}, T_{bot}))$, was created to minimize these delays. What the g function simply does is to increase priority to T_{Top} or to T_{Bot} according to the total volume already consumed.

After the application of this priority function in the temperatures, it successful decrease the previous difference between the reality and the estimation and decreasing the error rate, as it can seen in the graph below, Fig.3.11. The delay between the volumes graph lines almost overlap at some points making it hard to distinguish them.

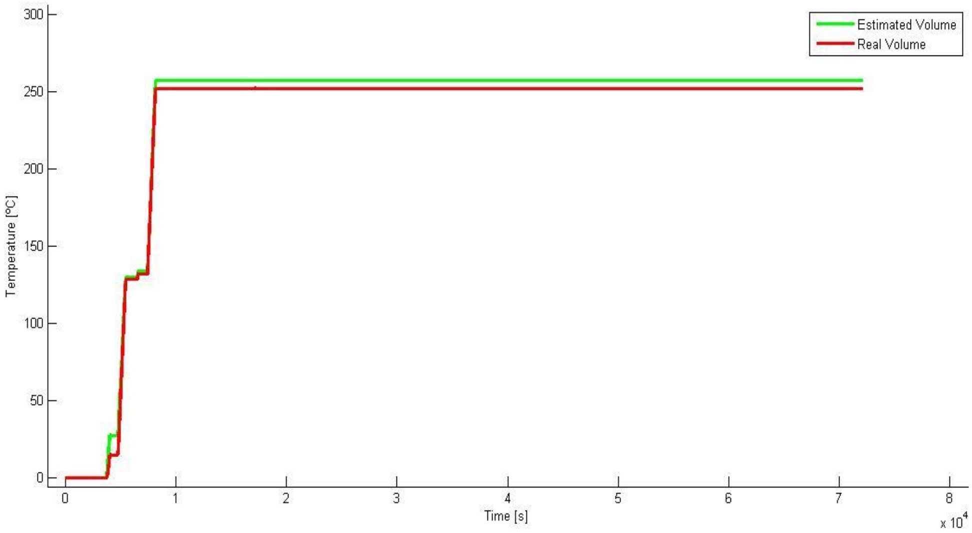

Figure 3.11 – Volume Estimation with Priority Function Vs Real Volume

The next graph, Fig.3.12, represent the different layer's temperature which are caused of by a tapped volume, it can be seen that is visible the thermal stratification between them is visible at the initial condition, there's a difference of more or less 5ºC from the highest layer to the bottom layer, and after the heating up.

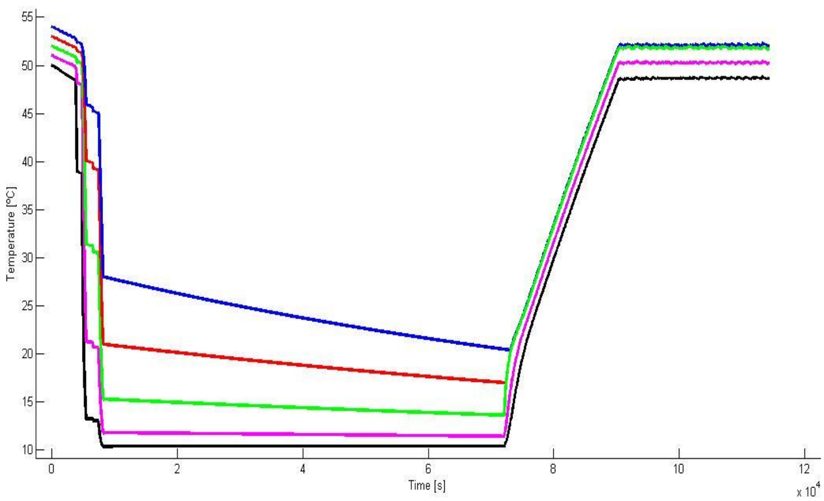

Figure 3.12 – Layers Temperature, a consumption cycle of 250L T_{ref}=54ºC; $T_{amb=}$10ºC;

3.3- Neural Network Design

Now that the ASHPW model is validated with reliable results between the simulation and the experimental results, it is then possible to move to the next stage of this development, the high level control, the new SC.

The main objective of this dissertation is to develop a new control Software, able to acquire information from the user profile (the client tapped profiles) in order to guarantee the maximum comfort, implementing in this way a smart controller with inherent COP increases of Heat-Pump appliances.

From the information that was gathered in the chapter of state of art about Neural Networks it is known that they have high capacity to learn from examples, extensive data and fast processing in parallel even high non linear complex systems and capacity to adapting and respond to environment changes.

These properties are very important for the objective purposed, since domestic water heaters are complex system, related with non linear processes, with ambiguous and different data that may influence the whole system. A Neural Network will be developed to work as a learning machine, learning the user tapped pattern profiles.

As on the modeling of the HP system, the Software “Matlab” will be used to design, train, validate and generate the NN. The NN toolbox provides some interesting and different architectures configurations to a variety of objectives, namely, Fitting App, Pattern Recognition, Clustering and Time Series App. The fitting app is aim to design a NN to map between a set of inputs and outputs targets. When it comes to pattern recognition, the target it’s to create an NN to classify the inputs into a set of target categories. In the case of clustering problems the NN groups data by similarity. Finally, Prediction is a kind of dynamic filtering, in which past values of one or more time series are used to predict future values. Dynamic neural networks, which include tapped delay lines are used for nonlinear filtering and prediction.

The first step to develop the NN is to define the data that it is desired to be collected from the appliance, as inputs, and the outputs, where it may or not do modifications so we to increase the COP and comfort increase. After choosing the inputs and output data, they may be correlated and then proceed to the Training phase, where samples are presented to the network and it is adjusted according to the error rate. The next phase is the validation step which measures the network generalization capacity. Finally the testing, which provides an independent measure of performance of the NN.

The first step is to choose the NN inputs. If the objective is to learn the water consumption profiles, it’s important to associate the quantity of water used each day of week. There will be two groups of days: the weekend and the week days, because of difference between the daily routines there are also significant water consumption difference patterns [19] [20].

Next inputs to develop more complex and strong relationship to the targets may be data which it is possible to have direct access in the HP at good reliability conditions. The temperature NTC sensors values, which also have high influence at the HP operation and COP results, and are also, correlated to the water loop consumptions and the water heating loop.

The following Fig.3.13 shows a brief illustration of what parameters it may be interesting to access and how we may implement than the smart controller.

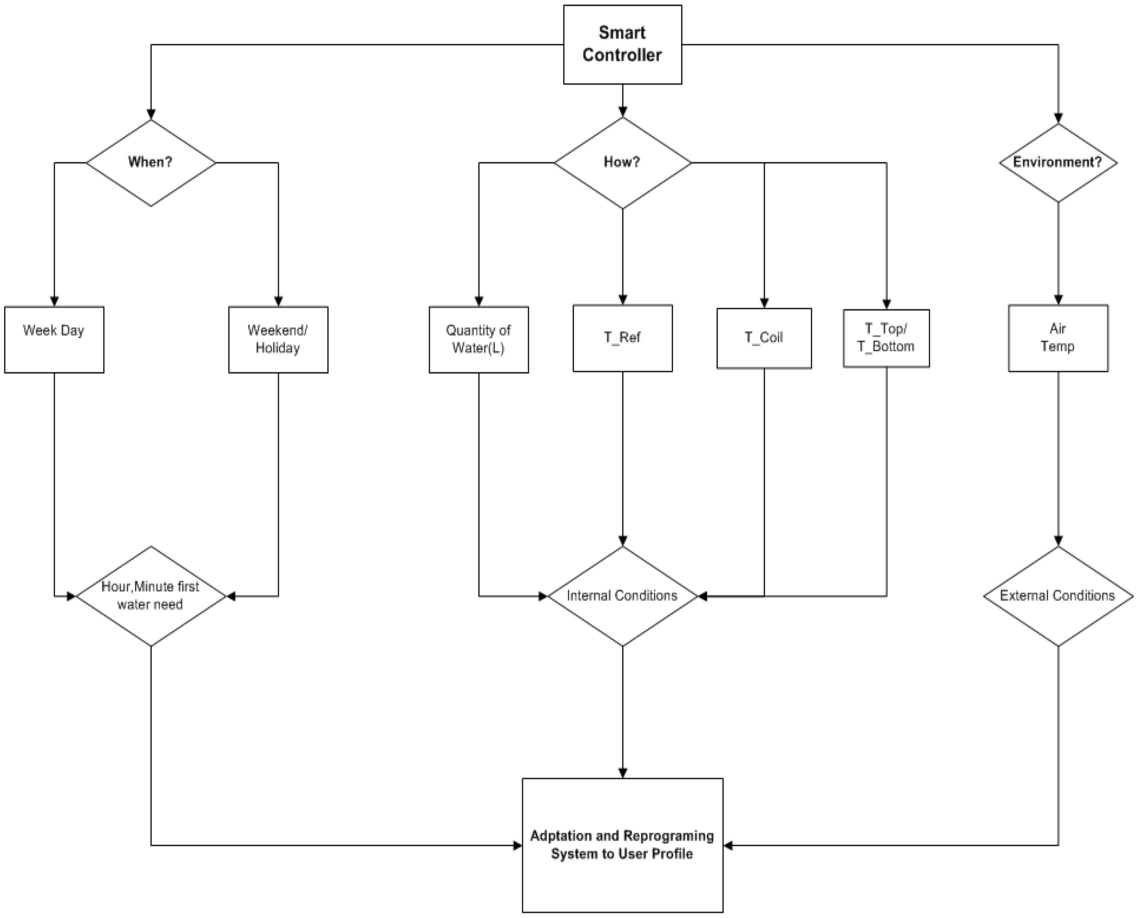

Figure 3.13 – Smart Controller Design

Water Consumption Pattern Profiles

To train the NN it is needed reliable data from user profiles. For that purpose and since there wasn't experimental long time data from benchmark available, with results from a typical family aggregated hot water utilization, a first research on user profiles the mean quantities of water used by families were made [19] [20]. After, the creation of these patterns the NN can be trained and later tested for the respectively dwellings.

The water consumption for each dwelling has been estimated per day. The estimated mean consumption is 122 Liters/Day. In the Fig.3.14 it's possible to see the results between the hot water consumption quantity of liters per day and the percentage from the houses that respectively do that consumption. The most common consumptions are in the interval from 50 to 125L which comparing to the HP tank capacity will be a medium or small consumption.

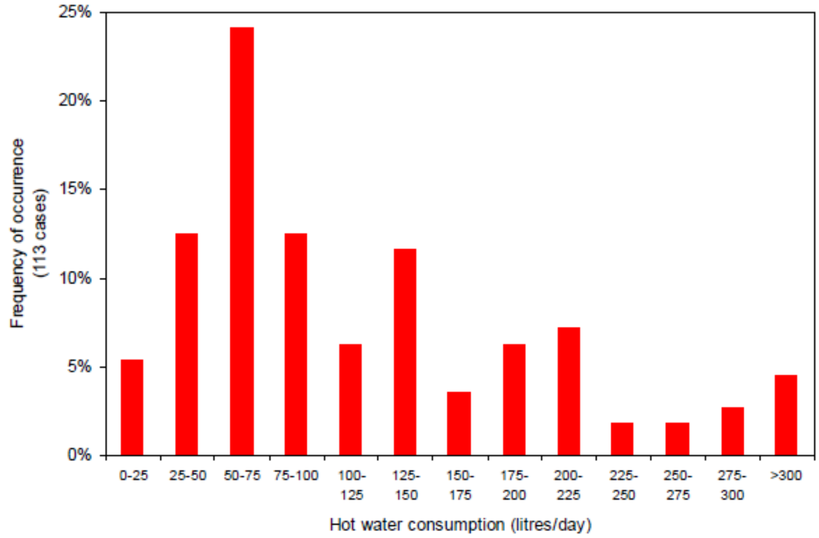

Figure 3.14 – Hot Water Consumption Liters/Day

However, this is the mean value of all families in the studied [19] and some influence factors must be taken into account, so a more detailed analysis to specific cases can be achieved. The factor that has the highest influence at the mean consumption is number of occupants of each house. Others parameters like the type of heating appliance or the geographical region have less influence and may not be considered significant factors, in daily water prediction. It will be taken a deeper analysis at the factor that can cause more difference, so in the graph below there's the relation between the liters of water consumed and the number of occupants.

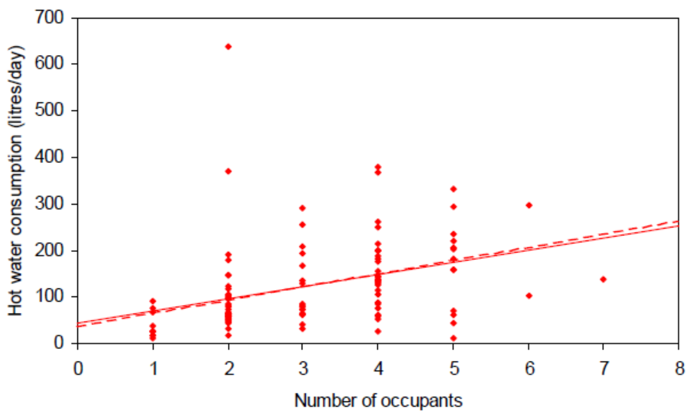

Figure 3.15 - Mean Water Consumption by Number of occupants

To develop the NN different daily water consumption patterns were created, with different number of occupants and consequently different daily water consumption. A family of two and four members was considerate. For the same family or house, daily water consumption was simulated with a final time of two to three weeks. Also, some variations in the volume consumed or even at time of the utilization and the flow rate, for the same day, were made. This will provide more realistic utilization patterns and a deviation which will serve to improve and to confirm that the future NN will have a good reaction even to some different or unexpected situations.

Air Temperature

Direct measured air temperatures, values and variations from Aveiro, Portugal (local weather daily acquisition rate with samples of 1 hour) with maximum, minimum and average temperature were provided by the company. The Data available from the year 2013 was collected in all days of the year with the previous referenced time step, Fig.3.16, so it is a reliable source data for every season of the year. Daily patterns were simulated with real air temperature, for different seasons of the year with high variation of mean temperatures.

Air temperature is very important in the mode of operation of the HP and to its performance. Normally higher temperatures mean will give higher COP.

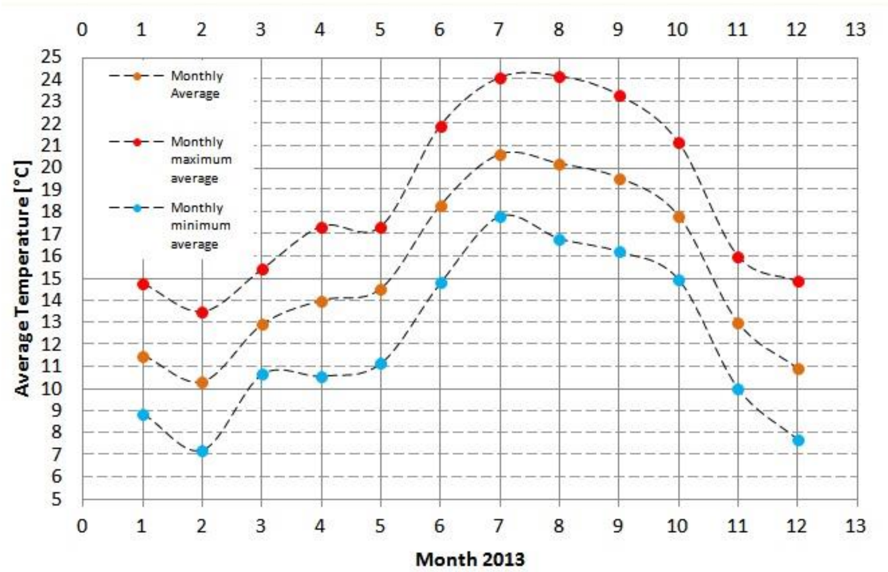

Figure 3.16 – 2013 Air Temperatures, Aveiro Portugal

3.3.1- NN Implementation

Now that the patterns are created and implemented on the learning machine responsible is ready to learn and adapt itself to the user water consumption, is ready to start.

Therefore the NN developed will relate the input day, and the output volume, the time scale resolution will be divided in small intervals. It will be considered a time step of k minutes (in which it may happen considerable water consumption) which makes 144 samples per day and total 1008 by week. This number of samples will offer a good relationship between the number inputs to train the NN and considerable but acceptable time to train the NN.

The inputs of the NN will be:

Day: Integer from 1 to 7 which will respectively represent the day of the week, from Monday to Sunday;

Time: Daily time, hour: minute, with a resolution of k minutes. There will be 144 intervals by each day, a total of 1008 per week.

The outputs of the NN will be:

Volume: Quantity of water in liters consumed by each k minutes step. In the real appliance the learning would be from the electronic estimation volume/flow from the algorithm to the electronic developed before. In the case of the simulation to have more reliability and trustfully data the water consumption patterns created were used.

Air Temperature: In the real appliance the input will be collected from direct measures from the NTC sensor present at the HP appliance at each K minutes step. In the case of the simulation, with the same objective to have reliable data and consequently good simulation results, the provided measures from a whole year with daily air temperature were used.

Now that the inputs and outputs data is defined, the design of the NN can be started, training it to fit the inputs and the outputs targets, followed by the validation and the testing phases. The learning time and data acquisition time to the NN considered were two weeks. So there will be a total of 1008*2=2016 samples. The data division was 80% to the train phase and 10% to the other following two. The used training method was the iterative “Levenberg-Marquardt”.

The layer architecture is a planar feed-forward. In order to define the numbers of hidden layers of the NN, the numbers of neurons at the layers, various network architectures have been investigated aiming to find the one that could result in the best overall performance. Although, “Matlab” only allows to change the number of neurons at each layer.

To evaluate the performance of the NN the results are analyzed with the MSE (Mean Square Error), the average square difference between the output and the target. Also the Regression values (R), which measures the correlation between outputs and the targets, a value close to 1 means close relationship, 0 means a random.

Thus, the results of the training phase had low MSE and almost a complete R relation, the same close relations were found for the phases of validating and testing. These results were considerable acceptable due to the variation and ambiguous input and output data.

The previous performance ratios could be improved with the used of more data, changing the learning time and the data used from two weeks to more time, like a month or even more. However, if it the NN would had seen significantly its performance increased, in the real system, one month may be a very long time where environmental conditions may had changed a lot or even the user habits due or not to environmental changes be different. Also, taking so much time to learn and then adapt the system to the user will make the learning machine slower and the improvements that we can achieve with it application would only start to take effect later, during time we could already being benefit from them.

Thus, a two weeks time were defined as the learning and data acquisition since the performance rates were already in good intervals. A one week was also tested but the results weren’t so satisfactory, due to the variations and the unexpected situations appearance.

After concluding the training, validation and testing phases, “Matlab” automatically generates a “Simulink” block that represents the NN relationship between the inputs and the targets. This block can be implemented now as superior level to control the previously HP model. To do so, it will be used the output of our NN connected to FLC, developed in the following, which will interpret the user profile and try to change and adapt the HP parameters in order to increase the comfort and the COP of the HP, Fig.3.17.

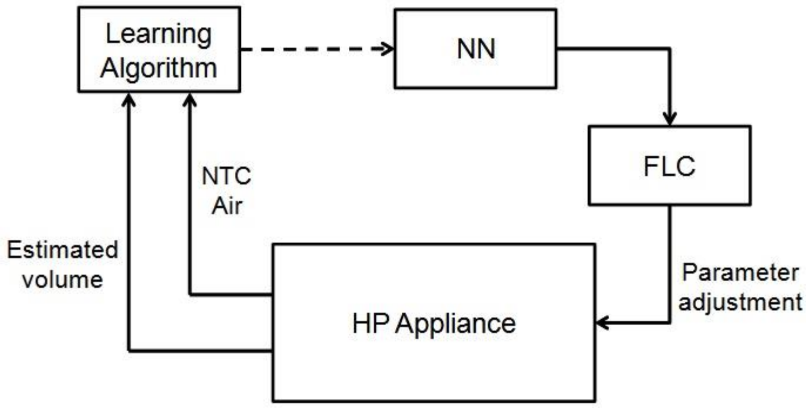

Figure 3.17 – Learning Machine

3.4- Fuzzy Logic Controller

The next step of the "Smart Controller" development is to integrate the FLC that will interpret, infer and decide based in human knowledge and expertise how to adjust the parameters of the HP to improve the COP and comfort.

To do so, the Software "Matlab" was also used, its capabilities and Fuzzy Logic toolbox to develop the MF's and the If-Then Rules.

The inputs of the FLC controller will be the outputs of the NN, the estimated volume and the air temperature learned from the previously two weeks, to that day, hour and step of ten minutes, which it will be used to predict and adapt the HP to react better to the expected water consumption.

3.4.1- MF's Definition

The first step of the FLC is the Fuzzyfication, where the inputs are acquire and translated the crisp values to MF's linguist variables. For that, it must first be constructed the MF's and theirs linguistic variables representations based on the previous studies, "common sense" and knowledge about HP appliances.

The air temperature is directly correlated to the HP heating mode. The appliance supports temperatures from 5 to 35 ºC to work as a heat-pump, and the higher this temperature is the more effective it will be the heating cycle. Even, if the water inside the tank is at higher temperature. It is measure directly from the NTC sensor and of course it cannot be separated from the weather conditions, even if the HP is at close compartment. Therefore, five linguist variables will be created to define the air temperature, respectively: Very Low (VL), Low (L), Medium (M), High (H) and Very High (VH) Temperature, in a range from 0ºC, where the HP doesn't even can operate normally, to 40ºC which from the air temperatures analysis don't occur often at the EU territory. The MF's to associate the linguistic variables will have the form present at Fig.3.18.

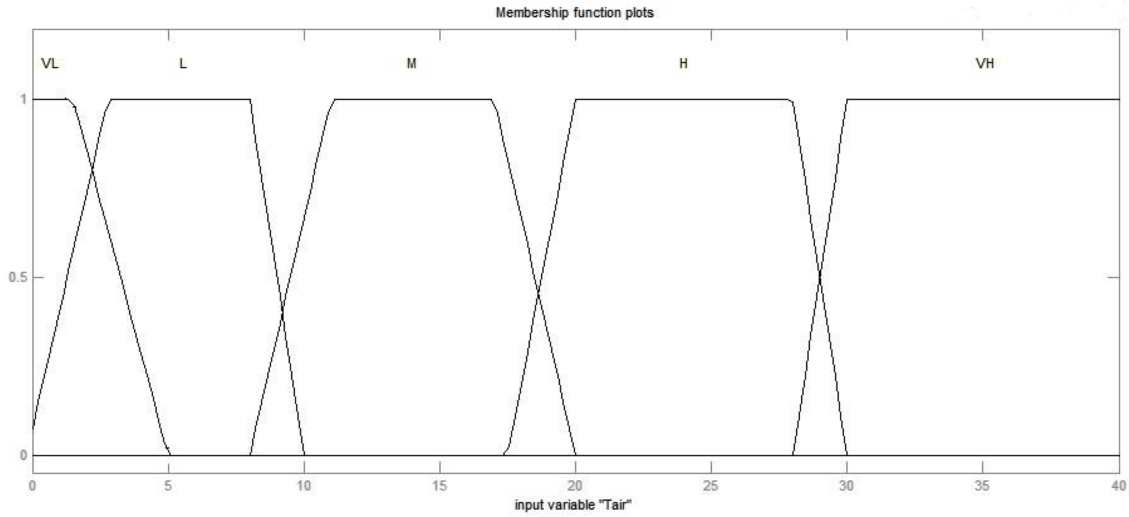

Figure 3.18 – Air Temperature MF's

To the volume consumption, learned at the NN, the previous studies done to the priority function g and the input volume influence to the water temperature will be also important as a base. To the construction of the MF's the flow rate will be taken into account to define the MF's and their relation to the volume, i.e. since our time step is 10 minutes in house it's very improbable to have consumption higher than 200 liters, physically even the house normal canalization wouldn't support much more flow circulation. In Fig.3.19 it can be observed the shape of the MF's. The linguistic variables are also Very Low, Low, Medium, High or Very High.

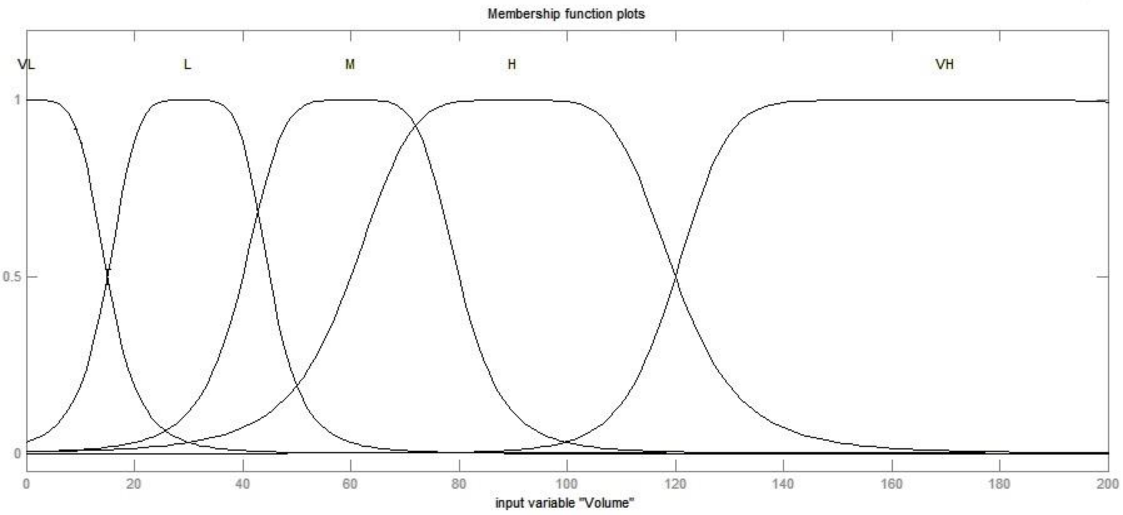

Figure 3.19 – Volume Consumption MF's

The output of the FLC will be the parameters that it is desired to adjust, in order to improve the COP and the comfort. The first approach will be to try to adjust and changing the temperature Set-Point of the HP, the Heating Mode or even to change the Heating periods programmed.

The standard set-point defined is as 54 ºC and usually the hot water delivery temperature is in the interval 48-60ºC to serve the minimum hot water requirements of the users. The point will be to change this set-point increasing, decreasing or maintain it accordingly to the volume. It will be taken into account the thresholds of water temperature comfort If the user has a low profile water consumption, there isn't need to heat up so much the water because the inlet water temperature won't be in big quantities, so the temperature won't decrease fast. The loses to the ambient are decreased due to the tank is at lower temperature, so the difference to the ambient will be smaller. Finally if the set point is lower the heating up will consequently being faster. Otherwise, if the consumption volume is very high it is wanted to increase the set-point in order to have the temperature higher inside the tank, so it will keep the water at good outlet consumption temperatures for longer, increasing the comfort, but also the water temperature gradient will tend to higher inflexion point. For some volume, the standard Set Point will suffer no change. The MF's functions and theirs linguist variables and the range are represented in the Fig. 3.20.

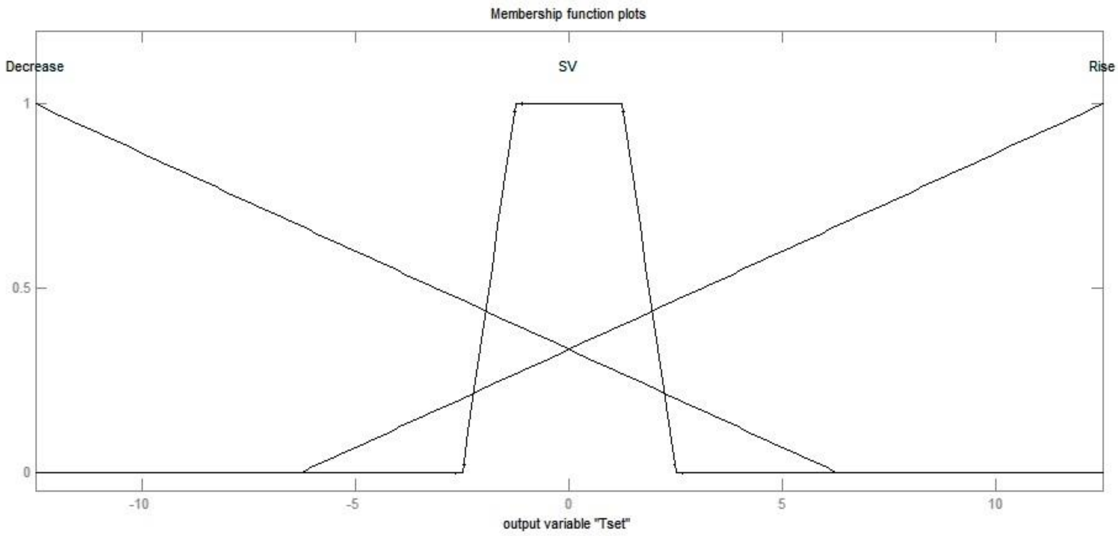

Figure 3.20 – Set Point Output MF's

The next output parameter that is going to be extracted and adjusted from the FLC will be the heating up times and the periods programmed to the HP work. The NN has been trained and can predict the air temperature during day, based in the days of training. The temperature of the air pulled to the heat exchanger has a great influence at the COP. The detection of higher air temperatures and the rearrange of the heating up periods to take advantage from these high temperatures will make the COP higher and the heating up time smaller. Nevertheless, this changing in the heating up cycles must be made with caution, because it shouldn't be done if there isn't need of hot water in a close time, or if won't happen a considerable volume, otherwise it may be contributing to the heat loses or wasting energy. The previously programmed heating up may be cancelled. In order to this it will be defined two simple MF's functions, Fig.3.21, with the linguistic variables: no change and/or activated. It will be defined as simple and almost binary relationship.

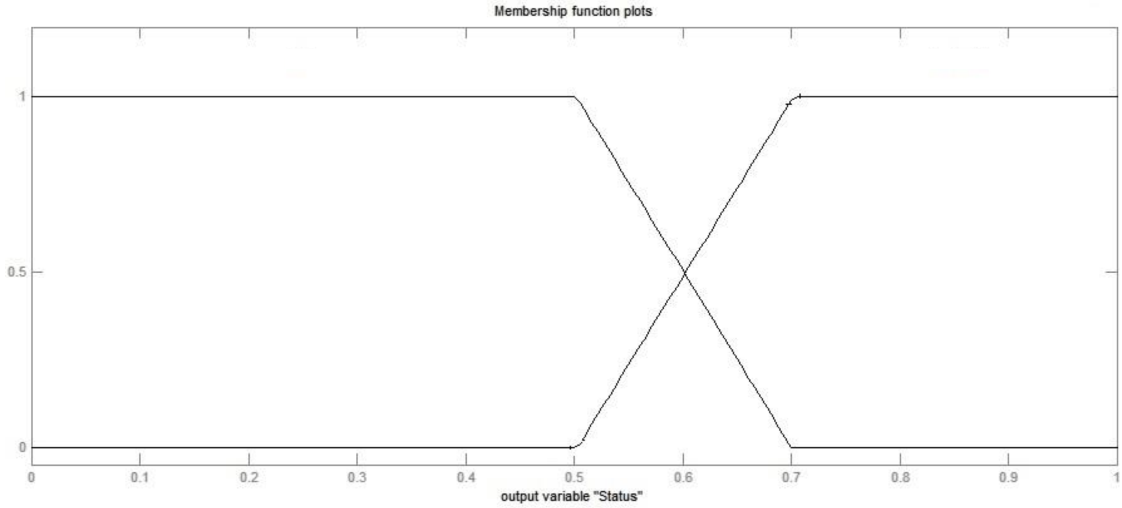

Figure 3.21 – HP Status Output MF'S

Finally the last parameter of the HP, to the FLC being developed to improve the HP appliance, will be changing and/or checking which of the HP operation mode is on. The most suitable to the quantity of water to be consumed soon or to the air temperature preview, will be activated. Changing between the modes according to the air temperature and the volume that will are predicted, may have influence at the comfort and even at the COP. It will be defined as simple almost a binary relationship, from a range from 0 to 1, Fig.3.22.

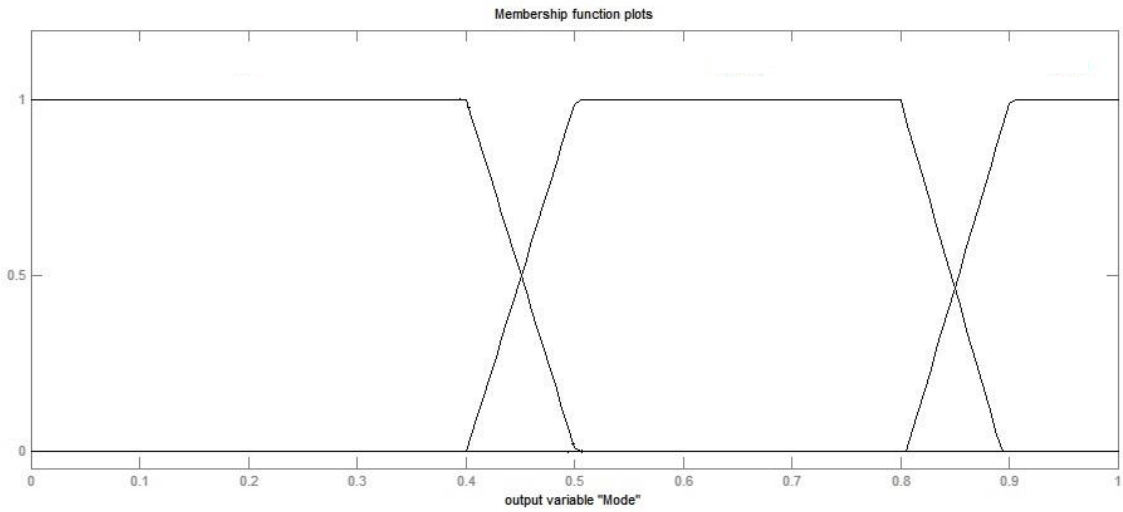

Figure 3.22 – Operation Mode MF's

3.4.2- Inference System

After designed the MF's and have the Fuzzy sets completely described, it's time to create the relation inputs-outputs to create the resulting region. A Mamdani inference system will be used to create the output region, a relation through an implication method for each If-Then rule, with different weights. The rules will describe the knowledge about the HP appliance and how it should adapt itself to the learning variables. A correlation between the inputs Volume and Air Temperature to decide what the FLC must do when it receives such linguist variables. Finally the final step, Defuzzyfication, to calculate the output value from the controller from the resulting region of the inference rules will be made by the Centroid method.

The output of the FLC is now ready to be used and to change the parameters in the HP appliance.

3.5. Controller Simulation

The controller is now ready to be implemented at the HP appliance, in order to first evaluate its security and the performance results. It will be firstly implemented at the model that was previously validated and capable to simulate the HP appliance. Thus, it will be possible to conclude if the controller developed will provide the desired improvements in the COP, the user comfort and energy saving, and to know if it pays off to develop the controller and step to its application at the real HP appliance, or if the FLC needs to be tuned up.

The high level simulation uses the HP process model and the controller structure that is achieved by linear block representation and the use of the Fuzzy Logic toolbox and the Neural Network toolbox, Fig.3.23, to transfer respectively the FLC, with the MF's and the If-Then Rules, and also the NN, fully trained for the period of two weeks with water consumption profile and the daily temperatures.

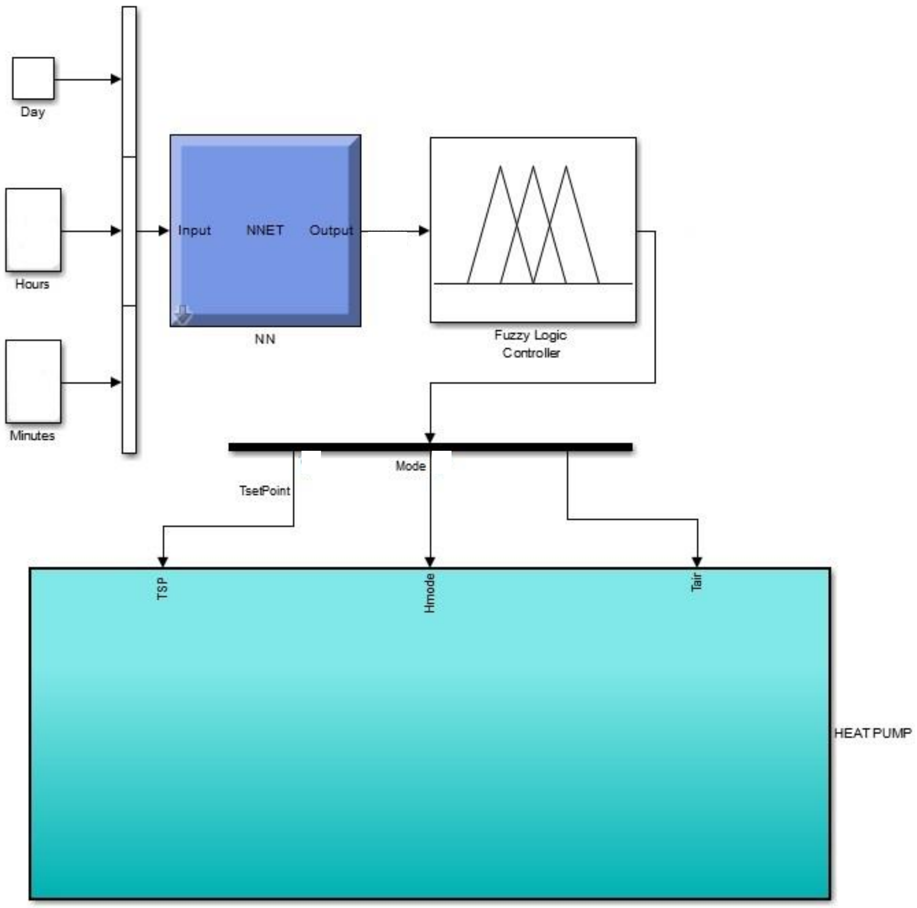

Figure 3.23 – Implementation Level Controller

The effect from the FLC different outputs, Temperature Set-Point, Heat Mode and Operation Status, will be analyzed independent at a first phase, and see if it provides improvements to the HP, if not adjustments at the MF's will be made, and at later phase the three outputs will be integrated.

The solution will be tested for the same profile patterns that trained and validated the NN, during a total time of one week simulation. In that way it will be possible to compare day by day and see to each one the direct influence of the FLC, moreover to analyze the all week results.

The Temperature Set-Point parameter influence to a specific day, during the operation system can be analyzed in the following graphic, Fig.3.24. It is possible to see that in the most of the cases the predefined set-point, 54ºC, was too high to the quantity of water that will be consumed in a short time. The FLC basing itself in the volume learned and outputted by the NN will lower its value. The new set-point will be a value that assures that the user will receive domestic hot water in good temperature comfort conditions.

With the variable set-point it will be possible to decrease the time that HP is working to achieve the Set-Point, but also the thermal loses to the environment due to the smaller difference to the temperature at the external.

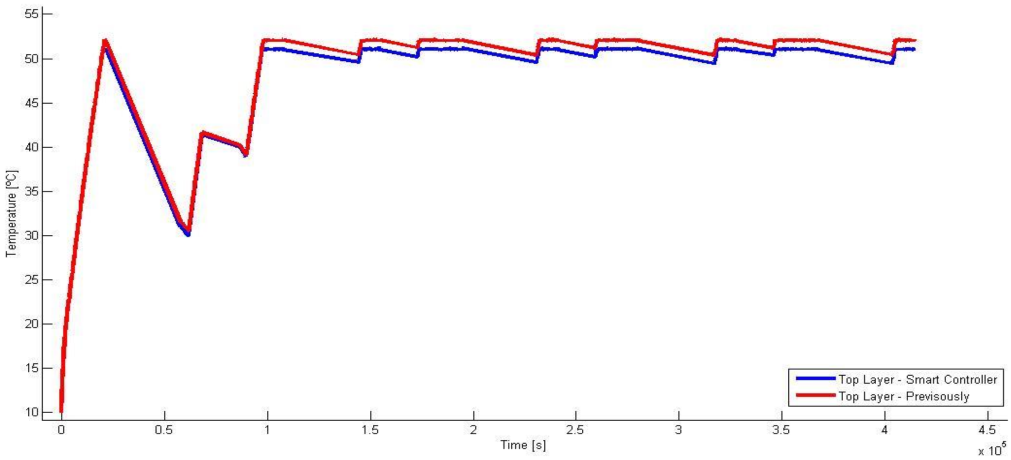

Figure 3.24 – Top Layer Temperatures, Smart Controller Vs No Controller

In the following, the time that the HP is working due to the fact that the set point was lower, and also controlled by the FLC with the Heat-Pump mode, will decrease. In the Fig.3.25, it is possible to check that the HP will stop providing Heat before it did without the SC. This will allow saving energy and improving the eco efficiency of it.

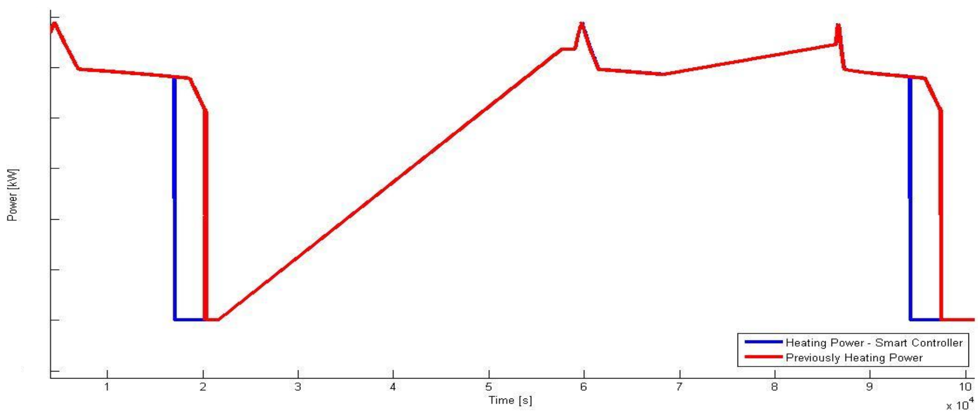

Figure 3.25 – Daily Heating Power, Smart Controller Vs No Controller

The energy saving observed in the Fig.3.25 will be obviously variable, it will depend on how much the Set-Point was lower and the volume consumption predicted. In the case presented the step difference is approximately 80 minutes between the HP stop times. This will be translated in to an energy saving directly from the Ventilator and Water Pump power consumption. The compressor which powers depends on the work need to be provided, function of air temperature and water bottom temperature will also be saved.

Following the Heat-Pump Heating periods will be changed in order to the external air temperature. When a high air temperature is expected by the NN prevision, the HP will start working, instead of at the only programmed periods taking advantage from the more efficiency periods. In the Fig.3.26 can be observed the predefined times to a day from the factory settings (0-HP OFF, 1-HP ON) and the new heating periods due to high air temperature prevision. The graphic with the daily temperatures related to the day analyzed is also presented. It is possible to observe that when a higher temperature is predicted the HP is also activated by the FLC taken it as an advantage.

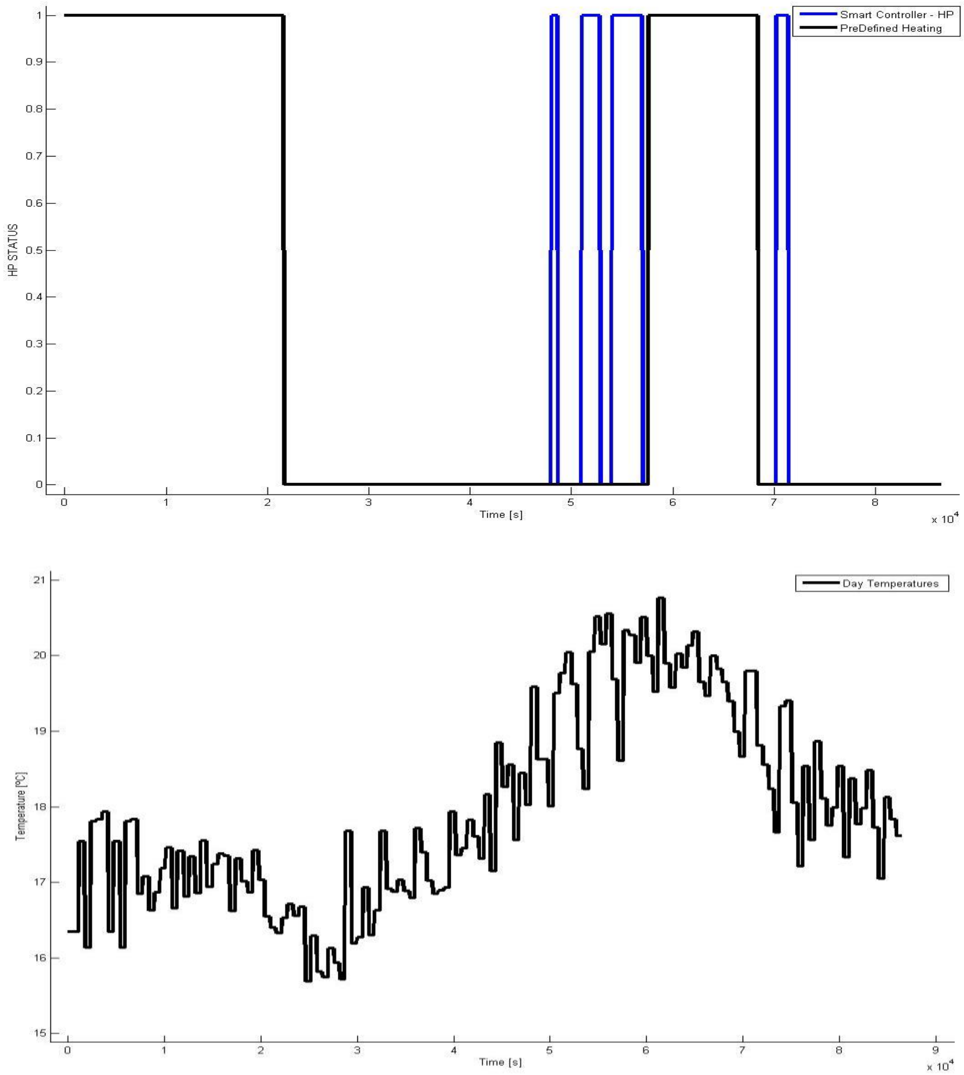

Figure 3.26 – a) Heat-Pump Heating Periods, Smart Controller Vs No Controller; b) Daily Temperatures

This new heating periods will contribute to improve the instantly COP and the heating transferred to the water, as the HP is working at times where the temperatures are higher. In Fig.3.27, is possible to observe and compare the thermal load of the new programmed heating periods and the previous ones.

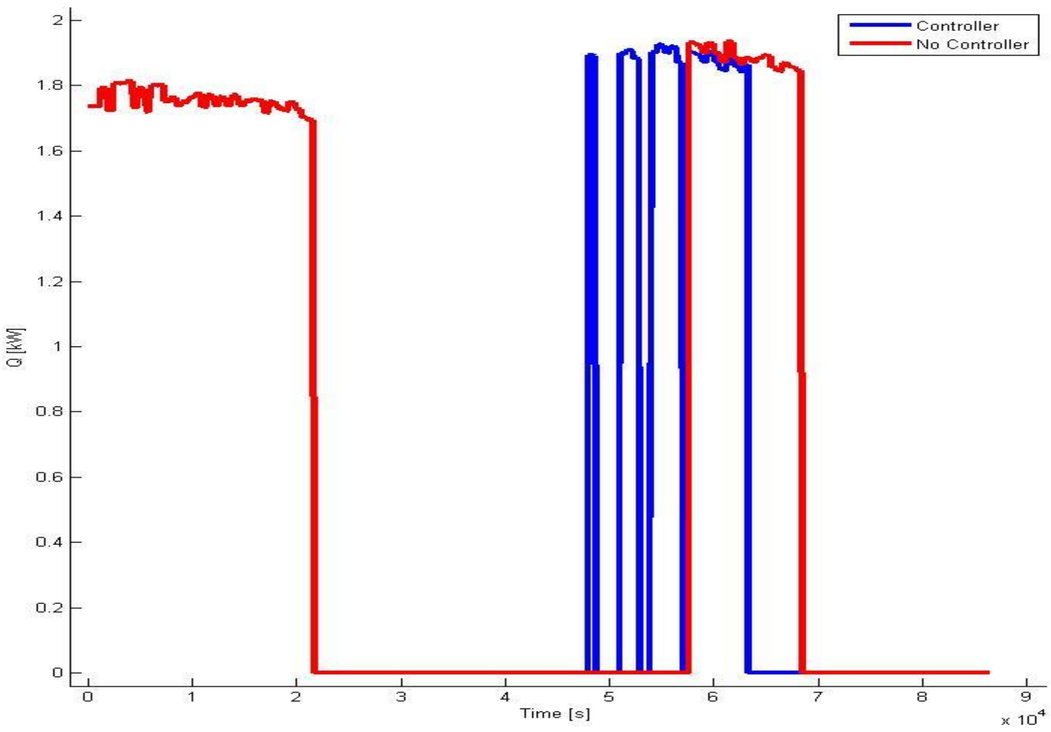

Figure 3.27 – Air FLC influence on Heating Power; SC Heating Power Vs Heating Power No Controller

Since it is been analyzed for the same daily and user tapped profiles, at the end, the heating provided by the Heating Module to the water, must be the same or very close with small error associated. It is due to the fact that the same quantity of water was consumed, so the same heating energy must be restored inside the tank. In the Fig.3.28 it is clear to observe that the final heats provided by the two solutions are close.

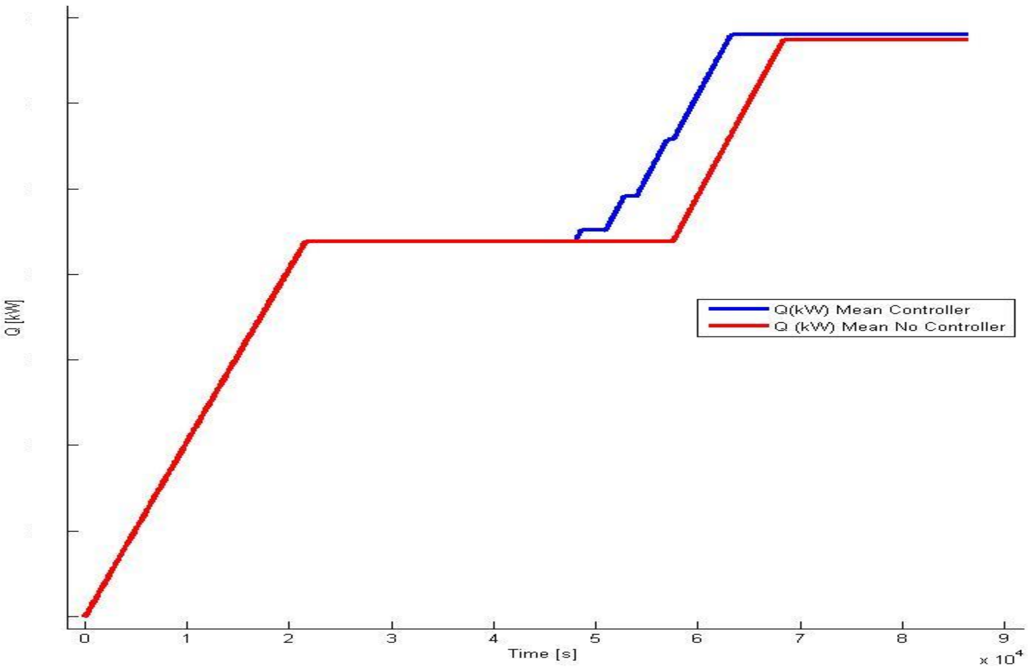

Figure 3.28 – Total Daily Heat Transferred, Q

The integration of the previously exposed parameters adjusting by the FLC will finally give result to a higher COP then before, as it can be seen in Fig 3.29, the daily COP with the Smart Controller to the learn user profile will be 15% higher than the previous.

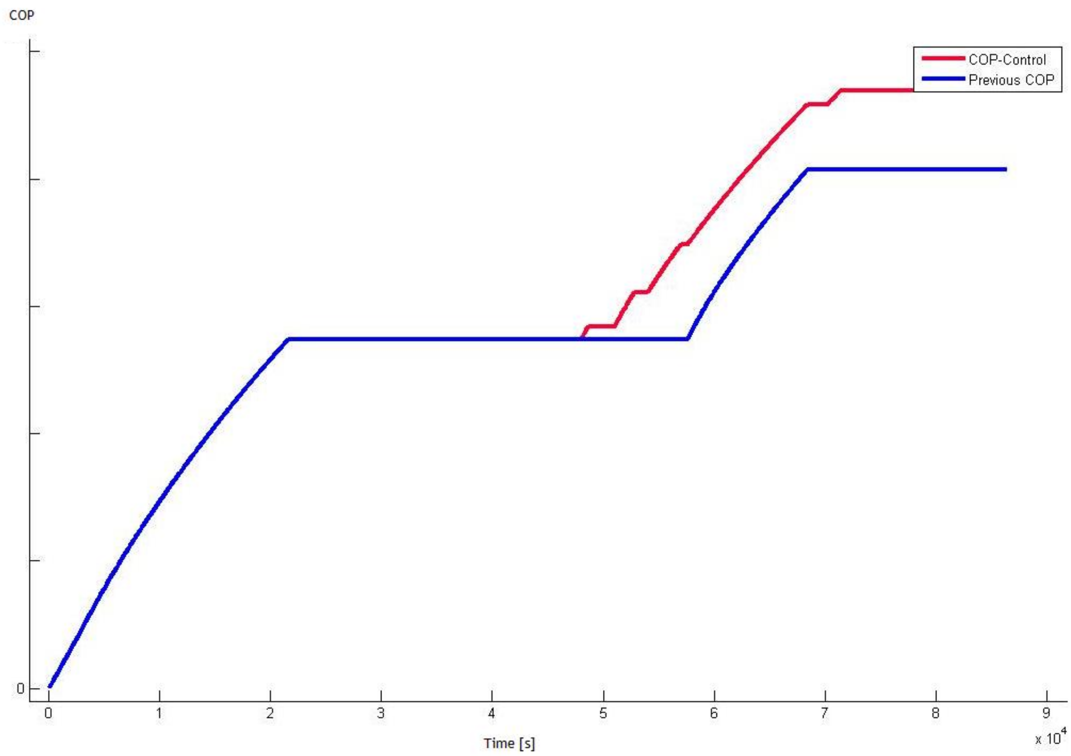

Figure 3.29 – Daily COP; Comparison COP SC Vs Previous COP

In summarizing, it was designed at the Software “Matlab”/”Simulink” an learning machine, which is capable to predict and to adapt itself to the water Volume consumption and the environment Air Temperature. The learning machine was constructed using the NN technology, using the capabilities of the “Matlab” Toolbox, with real air temperatures samples and different families and water consumption patterns.

In the following an FLC were designed which will interpret and inference at the outputs from the NN. It will adjust the Set-Point, the Heating Periods and the Mode of Operation of the HP. The MF’s and the If-Then Rules table were constructed with the previous knowledge and studies on the HP systems. The FLC will be able to keep the water at the desired temperature by implemented incorporating the user experience with the FR.

The integrated control solution, NN and FLC, acting on the HP model contributed to an improvement of the performance of the HP. Those improvements are rendered as the increase of the COP of the HP and energy efficiency and saving. The user will benefit from improvement comfort as the HP will recognize the consumption pattern and be prepared to satisfy its requirements of domestic hot water consumptions.

Chapter 4

Conclusions

4.1- Epilogue

In this dissertation it was described a solution to implement a Smart Controller for a HP. The design process, the results of a simulation with real experimental data are also described.

Initially, a research was done on the main issues to be addressed throughout the project. It was described the current state of art of HP high level control possibilities and capabilities, and an introduction to the operation of a heat pump of different types and the existing components. The main focus is given to ASHPWH as it is the type of pump where the controller will be implemented.

Incorporating a Smart Controller is intended in order to respect future exigencies of ERP and European Standards. The Smart Controller should be able to acquire information from the user profile and by implementing a learning machine and using a Fuzzy Logic controller it should be able to keep the water at the desired temperature. A study through the capacities and the potential in heating system was made. It was found that the response to high non linear system and incomplete or ambiguous data were very good so it has become as a good solution to be incorporated with traditional controllers.

Solutions from other studies published were evaluated as well as the techniques used to construct the controller incorporated and the learning machine. It is clear that fuzzy logic is widely utilized in solar heating water systems but its application on Hp system is not very frequent. Provided that the concept of water distribution and heating loops are very similar, some concepts and ideas can be correlated. The learning machine, based in neural networks, had been considered a major solution. Their use also increased in the last years with application to multiple objectives in the energy field, most commonly COP prediction, energy consumption or response to environmental conditions.

After literature review it was implemented an one-dimensional thermal stratified model with computational artifices in order to describe the complex operation of a heat pump with the interferences of water and temperature flow, but also the loses, the heating module and the mode of operation. The model was built with all indentified system constraints and nonlinearities. It was obtained very good results and performance, comparing the model results with experimental real data, in different operations conditions and long time simulations. The errors were always lower than 5%. It was verified a good and capable to be used in the simulation and tuning of the controller.

The NN developed was trained, tested and validated with real data and experimental. Different user hot water consumption profiles patterns were created from the studies with typical and real information.

Therefore by using the output data from NN as inputs of the FLC and integrating the learned information on the HP it is possible to predict the future needs of the HP user. In that way, it is possible to prepare the HP system to respond better than without knowledge about the user typical pattern. To do so the parameters Set-Point, HP heating periods and Heating Mode were adjusted and changed in order to improve the HP efficiency by the inference.

The integrated solution proposed, NN and FLC, as the new software provided increase of the total COP of the HP system and also energy efficiency and saving. The FLC can arrive to improve the COP of the HP by 15% comparing to previous simulation results without the SC.

4.2- Future Work

There is still work that can be done in order to improve the use of the Smart Controller, and the use of the learning machine in order to improve the COP and the user comfort. Some suggestions for future developments are presented:

- Include Electric tariffs values: the NN should be able to learn and adapt itself to the electricity price. The electricity price and the quantity of electricity usually consumed should be learned and later a FLC that taken into account that information and could perform changes, in the time that the HP is working or the mode it is. That way it would probably contribute to decrease the electric bill of the customer, decrease the energy consumption and improving the efficiency.
- Implementation of the FLC at the real HP appliance: development of the code and programming of the microcontroller that is integrated and responsible for the HP operations, measuring and control.
- Integration of more NTC sensors at the HP appliance. The more measures acquired from the water tank layers temperatures the better thermal stratification phenomenon will be detectable to the electronic which is responsible to estimate the flow. Alternatively a flow meter could be used, so the flow would be measure directly, but this would increase the price of the HP.
- Exhaustive Fuzzy parameters tuning for better HP operation and parameters tracking which can promote the FLC response.
- Testing in a real HP appliance with the same pattern consumption profiles. To verify if the simulation results from the “Matlab” and “Simulink” model integrated with SC are also verified at the real HP appliance.

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